AN APPLICATION OF PREDICTIVE VEGETATION MAPPING TO MOUNTAIN VEGETATION IN SWEDEN

A Thesis

by

JANET ALEXIS GREEN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2005

Major Subject: Geography

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Approved by:

Chair of Committee,	David Cairns
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ABSTRACT

An Application of Predictive Vegetation Mapping

to Mountain Vegetation in Sweden. (December 2005)

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Chair of Advisory Committee: Dr. David Cairns

Predictive vegetation mapping was employed to predict the distribution of vegetation communities and physiognomies in the portion of the Scandinavian mountains in Sweden. This was done to address three main research questions: (1) what environmental variables are important in structuring vegetation patterns in the study area? (2) how well does a classification tree predict the composition of mountain vegetation in the study area using the chosen environmental variables for the study? and (3) are vegetation patterns better predicted at higher levels of physiognomic aggregation? Using GIS, a spatial dataset was first developed consisting of sampled points across the full geographic range of the study area. The sample contained existing vegetation community data as the dependent variable and various environmental data as the independent variables thought to control or correlate with vegetation distributions. The environmental data were either obtained from existing digital datasets or derived from Digital Elevation Models (DEMs). Utilizing classification tree methodology, three model frameworks were developed in which vegetation was increasingly aggregated into higher levels of physiognomic organization. The models were then pruned, and accuracy statistics were obtained. Results indicated that accuracy improved with

increasing aggregation of the dependent variable. The three model frameworks were then applied to the Abisko portion of the study area in northwestern Sweden to produce predictive maps which were compared to the current vegetation distribution. Compositional patterns were critically analyzed in order to: (1) assess the ability of the models to correctly classify general vegetation patterns at the three levels of physiognomic classification, (2) address the extent to which three specific ecological relationships thought to control vegetation distribution in this area were manifested by the model, and (3) speculate as to possible sources of error and factors affecting accuracy of the models.

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INTRODUCTION

In light of increasing concern for environmental issues facing the global population during the past few decades, much recent research in vegetation science and related fields has been driven by the desire to understand the processes that control biogeographic patterns at various scales. Within the unique context of currently growing awareness of the potential effects of anthropogenically-induced global climate change, knowledge about how vegetation responds to environmental factors and how it may respond in the future becomes crucial. While many ecological processes are as yet not fully understood, some understanding has been gleaned from studying how vegetation may have responded in the past to environmental changes, as well as how plants respond at the physiological level. Historical vegetation changes are often reconstructed using paleoecological evidence such as pollen analysis, while physiological processes are normally studied through laboratory or field experiments. Though an understanding of historical and physiological processes can help understand ecological relationships at a relatively fine scale, it is difficult to assess how various factors interact at the ecosystem level with these methods. This is because historical evidence is always limited in spatial extent to areas which lend themselves well to being sampled or studied, and experimental responses are often inherently species- and site-specific (Tjoelker et al. 1998), making extrapolation of responses to broader scales difficult or misleading.

This thesis follows the style of the *Journal of Vegetation Science.*

Larger scale vegetation responses are instead often best understood through the use of various ecological modeling techniques. Researchers in various fields have noted that if progress is to be made in understanding how ecosystems operate under climate change scenarios, studies must be conducted that are larger in spatial and longer in temporal scale and take into account multiple interacting direct and indirect effects of these changes (Oechel et al. 1994). Besides being able to assess vegetation dynamics at larger scales, models also have the unique ability to integrate knowledge from both historical and physiological methodologies.

Predictive modeling is especially applicable to these sorts of studies. Though an analysis of the potential effects of climate change on vegetation warrants a separate treatment, it is revealing to note some of the current thoughts on the matter so that future modeling efforts can be directed toward addressing some of the concerns. A major finding in paleoecology is that range shifts in plant species and biomes have been shown to occur in association with cyclical glacial-interglacial periods of the past (Davis and Shaw 2001). It is widely assumed that range shifts are occurring and will continue to occur in the future under changing climate. A significant concern of these range shifts is that due to the unprecedented rate of climate change foreseeable in the future, this may result in maladaptation in local populations in which climate changes faster than vegetation can genetically adapt to it or migrate, thus leading to the loss of genetic diversity (Davis and Shaw 2001). These vegetation changes may consequently affect entire ecosystem function. The nature of these vegetation shifts will most likely be that

southern species (or taxa – that include subpopulations within a species) will invade sites located at the present northern range limits of more northern species and outcompete the northern species. This is predicted to occur as opposed to northern species migrating northward and to higher elevations, because most trees are limited by physiological tolerances to extreme cold as opposed to heat, and as temperatures are warming, there would be no need for existing trees to migrate or seek refuge. Thus northern species would be able to survive in warmer climatic conditions, but because they have adapted a tradeoff between growth rate and cold tolerance, they are expected to not grow fast enough to successfully compete in the newly warmed territory from encroaching southerly species (or other taxa including populations within a species) (Loehle 1998; Aber et al. 2001).

Areas thought to be of particular geographic importance for studying the effects of global climate change are areas of higher latitude and altitude. It is thought that temperature increases will be most pronounced at higher latitudes and altitudes (Pastor and Post 1988; Grogan and Chapin 2000) and hence it is thought that these areas will exhibit the most pronounced range shifts in vegetation. The study area (Fig. 1) lies within a latitudinal and altitudinal zone that is thought to exhibit more sensitivity to climate changes than more low-lying and low-latitude areas due to the fact that vegetation in these areas are growing at their range margins in environments at the limits of their physiological tolerances, close to thresholds where survival becomes impossible. In addition, tundra and boreal ecosystems are thought to actively participate in the

dynamics of important greenhouse gases, as well as possibly generate biospheric feedbacks in response to climate change (Lenihan & Neilson 1993).

STUDY AREA

The study area stretches along the western border of Sweden in the Scandinavian mountain range (also known as the "Scandes" mountains). The Scandes mountains in Sweden reach a peak altitude of 2,111 meters at Kebnekaise (CIA World Factbook: *http://www.cia.gov/cia/publications/factbook/geos/sw.html*). The portion of the mountains within Sweden encompasses a broad latitudinal range. Climatically, the mountains predominantly lie within what has been classified as the Northern Boreal zone, but there is some southern and eastern extension into the Middle Boreal zone (Sjörs 1999). Alpine and subalpine vegetation dominate the Scandes mountains, in which a mosaic of forests, mires, and lakes exists (Engelmark & Hytteborn 1999). The upper forest line in the mountains consists predominantly of *Betula pubescens* spp. *czerepanovii*, or mountain birch, and ascends to about 600 meters in northern areas, and 800-1000 meters in more southerly locations (Carlsson et al. 1999). Coniferous trees such as *Pinus sylvestris* and *Picea abies* form a lower forest line in areas further south than the Birch treeline, ascending to about .

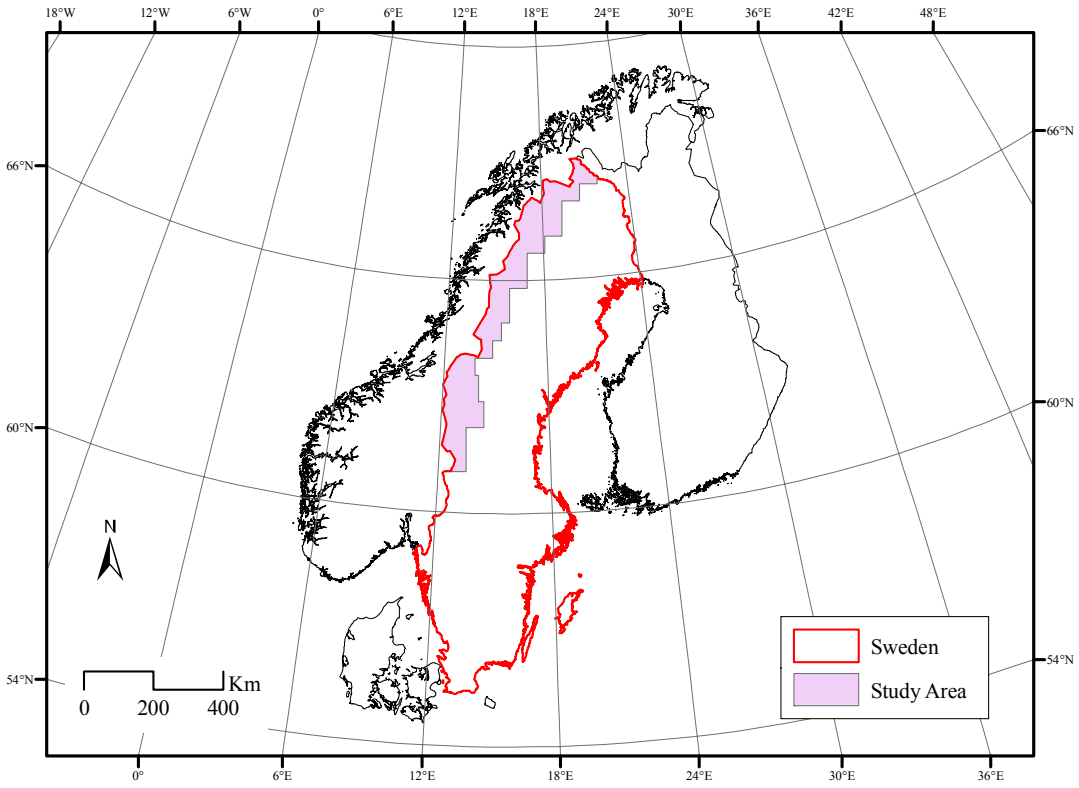

Fig. 1. The study area in the Scandinavian Mountains, western Sweden.

BACKGROUND OF PREDICTIVE VEGETATION MAPPING

Computerized predictive vegetation mapping or modeling (PVM) is a technique widely employed in the fields of biogeography and landscape ecology that began in the mid-1970's, experienced a surge of popularity beginning in the late 1980s, and continues to be widely applied today. The development has been driven by the need for environmental planning using large spatial vegetation datasets and for basic research on the role of the biota in earth systems science (Franklin 1995). PVM rests on the conceptual premise that naturally-occurring vegetation patterns can be predicted from the spatial distribution of environmental variables that control or correlate with plant distributions. The methodological background for predictive modeling of vegetation is gradient analysis and ecological niche theory (Kessell 1976), which will be discussed in more detail later. PVM is made possible by the increasing functionality of geographic information systems, remote sensing, statistical techniques, and availability of digital maps or spatial data of environmental variables of interest. Being highly versatile in approach, PVM is a powerful tool for exploring vegetation-environment interactions for research, planning, and pedagogy.

In a review of different ecological modeling methods, Guisan & Zimmerman (2000) make the important point that "Nature is too complex and heterogeneous to be predicted accurately in every aspect of time and space from a single, although complex, model". Each model has its strengths and weaknesses, and the choice of model depends on the

purposes driven by the research questions. Sometimes the purpose is to map the potential distribution of vegetation for ecological restoration or biodiversity conservation planning or to assess the potential impacts of environmental change on vegetation distributions. PVM has been used in the past to aid in classifying vegetation when remotely sensed images are not high enough resolution to classify vegetation. Used in conjunction with remotely sensed data, PVM can provide ancillary information on the vegetation that cannot be gleaned from the analysis of imagery (Franklin 1995). In conjunction with the recent surge of interest in the potential effects of climate change, PVM has been widely used in both understanding climate-vegetation relationships and predicting how vegetation patterns will change in response to climate change. Because different species and assemblages of vegetation respond differently to environmental influences, it is useful to perform case studies incorporating models that elucidate the unique reactions of different species and communities to different environmental controls.

The closest geographic location to the study area documented to utilize PVM is a case study of Norwegian mountain vegetation in which 107 species of vascular plants were predicted in relation to thermal parameters (Sætersdal & Birks 1997). The current case study of vegetation composition and distribution in Sweden will attempt to supplement current understanding by exploring the relative importance of underlying environmental variables that control vegetation community distributions and physiognomic types in the Scandinavian mountains of Sweden, an area not previously assessed using PVM studies.

Furthermore, the model will be assessed for its ability to correctly classify vegetation types. The results of this study could be applied to other areas with similar environmental constraints, or could be expanded upon within the current study area to predict vegetation changes in response to expected climate change.

CONCEPTUAL FRAMEWORK

Compositional patterns of vegetation are often predicted using PVM. Compositional attributes can be predicted at many levels of organization. Some studies predict vegetation at the species level of organization, while others predict communities or assemblages of vegetation. One study employing PVM methodology predicted vegetation at the formation, or biome level using climatic determinants, claiming that this level of organization is the scale that most directly interacts with the atmosphere (Lenihan & Neilson 1993). The choice of what level of organization to predict is often dictated by the availability of data rather than loyalty to any one ecological theory over another (Franklin 1995). Vegetation data aggregated to vegetation community types were used as the dependent variable in this study partly because these data were available, but also because the processing of data at the species level of organization for an area the size of the study area would require a huge amount of time and computational power, and therefore would be logistically unrealistic. Notwithstanding these limitations, it is prudent to understand the underlying theoretical debates

concerning how vegetation is thought to respond to the environment, because it would conceivably be more ecologically sound to predict vegetation at the level of organization at which ecological processes are thought to correlate with or control vegetation patterns. While this would make sense in theory, it is problematic in reality for a couple of reasons. Primarily, the way in which the environment controls vegetation patterns is often not fully understood. It is still unclear as to how vegetation responds to environmental factors as far as whether species respond individualistically (Gleason 1926) or as functional groups, assemblages, or communities of species. Currently, the Gleasonian theory has gained a substantial foothold in plant ecology (Sætersdal & Birks 1997), but the notion of communities or assemblages with possible functional characteristics, with roots in the idea of organismic ecology proposed by Clements (1915) has not been entirely abandoned (Turner et al. 2001).

PVM has its roots in the theories of gradient analysis (Whittaker 1973) and ecological niche theory (Hutchinson 1957, Austin and Smith 1989). Gradient analysis was developed from the continuum concept (Whittaker 1951), an idea that is linked back to the Gleasonian school of thought. Gradient analysis provides a way of describing and understanding spatial relationships between vegetation and one or more environmental, resource, and/or temporal gradients. The nature of the response of vegetation to environmental gradients has been widely debated within the field of plant ecology. An interesting claim was made by Brown et al. (1996), who pointed out that species generally find one side of an environmental gradient to be physically stressful due to

abiotic factors, and the other side to be biologically demanding due to biotic stressors. The majority of gradient analyses appearing in the literature are presented as justification for the individualistic-continuum response of species to environmental gradients, though one author notes that patterns arising from these studies are only correlative and do not preclude the existence of positive interactions between species that affect the functioning and subsequent distribution of communities as a whole (Callaway 1997).

Like gradient analysis, any discussion of ecological niche theory necessarily calls upon the debate personified by Clements and Gleason. Despite the lack of consensus regarding the compositional level of organization at which vegetation responds to gradients, niche theory purports that vegetation hypothetically will distribute itself in space based on fundamental niches, where the abiotic environment provides the most hospitable conditions for growth, but in reality it will be located in realized niches which take into account biotic interactions such as competition between species, herbivory, and disease (Austin & Smith 1989).

When predictive models are trained using actual extant vegetation, it follows that interpretation of predicted vegetation patterns must take into account that what is being predicted are realized, rather than the fundamental, niches. One must therefore take into account that the biotic interactions and disturbances that create the vegetation patterns observed in the dataset used to calibrate the model will likely change through time and place. With this in mind, application of the model to different times and places may be

unsatisfactory. Still, if the predictive model relies on existing vegetation data, it is this data that is used to calibrate the model. Existing vegetation represents the realized rather than the fundamental niche of vegetation. Mechanistic models are based on the fundamental niche of vegetation, while correlative models rely on the realized niche. Correlative models cannot predict patterns of vegetation based on the fundamental niche, because the fundamental niche is a theoretical abstraction rather than a concretely observable phenomenon, and research design of correlative models by its nature relies on vegetation information that is observable in the real world. It follows that even if data representing the manifestation of the fundamental niche were available to be used in these types of models, the resultant predictions would not be particularly useful anyway, as the patterns would not reflect potential realistic patterns, but rather a theoretical pattern only sometimes or maybe even never applicable to potential real world patterns. Consequently, while the use of extant or past vegetation patterns to calibrate the model may preclude or make difficult the extrapolation of results to different locations and times, Franklin (1995) points out that it is acceptable to use the results to predict vegetation within the area hosting vegetation that the model was calibrated from, as it is assumed that processes will play out similarly in the same general geographic area.

As discussed, PVM studies that predict compositional patterns of vegetation must be interpreted with the understanding that results from one area are not necessarily applicable to other areas or times, and are more applicable to interpolating within the geographical area of the calibrated data (Franklin 1995). A possible way to get around

this theoretical constraint is to model a different aspect of vegetation whose geographic distribution is more dependent on climatic and geologic (abiotic) factors as opposed to biotic interactions or disturbances. Such treatments predict vegetation structure or life form (physiognomy) rather than floristic components (Woodward 1987, Neilson et al. 1992, Prentice et al. 1992, Lenihan, & Neilson, 1993). When vegetation structure or physiognomy are used as measures of vegetation, species-specific responses are de-emphasized in favor of responses affecting all species of a particular physiognomy. It is understood that climatic factors, particularly thermal properties, structure vegetation at this aggregate level of organization (Prentice et al. 1992, Neilson et al. 1992). For instance, the global transition from forest to tundra vegetation is controlled to a large extent by temperature patterns (Sirois 1992). Therefore, in predicting structural or physiognomic characteristics, the problems inherent when conceptualizing species' fundamental/realized niches, as well as the confusion inherent in deciding between community vs. continuum approaches is avoided in practice, because no matter how it is patterned across the landscape floristically, all vegetation is subject to changes in structure and physiognomy due to the influences of climate at the broadest scales. Modeling studies exploring factors that control the location of treeline are examples of the use of vegetation structure/physiognomy as the dependent variable (Walsh et al. 1994), as treeline is located at the ecotone between vegetation dominated by trees to vegetation dominated by shrubs or tundra vegetation types.

The objectives of this study involve utilizing a predictive vegetation model to predict the distribution and composition of vegetation in the Scandinavian mountains of Sweden at three levels of physiognomic aggregation to determine (1) which environmental variables may be important in explaining vegetation patterns in the study area, and (2) how well the model predicts vegetation composition in the study area, and (3) how the amount of physiognomic aggregation affects the accuracy of the model.

METHODS

DETAILS OF THE MODEL

The type of model used in this study is a classification tree. Within the statistical literature, this type of model is described as a multivariate technique used to model proximity data by way of matrices of similarities or associations among entities (Corter 1996). For this application, classification trees constitute a member of a larger group of machine-learning methods that make up one of the main types of predictive vegetation models (Franklin 1995). Machine-learning techniques involve classification of categorical or continuous dependent variable(s) based on values of the independent variables and sets of rules determining how the data are split. Unlike other machine-learning methodologies, classification trees employ an approach that is exploratory, or essentially inductive, in that the splitting rules are developed during the modeling process rather than beforehand. Classification trees entail binary recursive partitioning of the dataset. They are flexible to many applications because they are non-parametric, assuming no a priori distributional characteristics inherent in the data, and independent variables can be continuous, grouped into ordinal classes, or categorical or nominal variables. Classification trees are closely related to regression trees, and the two are often presented together in the literature and described as "CART"s, or classification and regression trees. The only difference between these two model frameworks is that for classification trees, the dependent variable is categorical, producing a qualitative

response, and with regression trees, the dependent variable must be of ordinal or continuous data type, producing a quantitative response (Breiman et al. 1984).

Classification trees iteratively split the dataset such that each successive split contains fewer and fewer observations. These splits are called "leaves", and their numbers increase as the dataset is split further and further. The criterion for determining how the dataset is split involves determining the "minimum reduction in deviance over all allowed splits of all leaves" (Venables & Ripley 1999). In other words, the dataset is split such that the two datasets created from the split contain observations that are the most similar, or homogeneous, *within* one of the datasets, and the least similar *between* the two datasets. When a tree is first created, it is "trained", or calibrated based on the peculiarities inherent in the particular dataset that is used to train the model. For this reason, it produces splits in the tree that contain very few observations, rendering the model not accurately generalizable to other datasets (Venables & Ripley 1999). In order to resolve this problem, once a tree is created, it is normally "pruned" to eliminate extraneous leaves of the tree in which the model is "over-fitted" to the particular dataset used to train it. Pruning is performed on the datasets in this application using a procedure known as cross-validation. This procedure uses a separate dataset called the "validation" dataset to determine how far the tree is pruned (Venables & Ripley 1999). Using this dataset, the tree was pruned until subsequent splits resulted in minimal overall improvement of model predictions.

MODEL ASSUMPTIONS/LIMITATIONS

As with any model, predictive vegetation models necessarily entail a simplification of reality where certain assumptions or limitations are an inevitable part of the modeling process. One aspect of classification trees that could be considered limiting is that they are correlative rather than explanatory. This means that the underlying ecological processes and interactions between environmental variables are not explicitly explained, or taken into account in any mechanistic way, by the model. There are other types of predictive vegetation models that do take processes into account in this way, but they are often restricted to finer scales of analysis such as individual forest stands or trees, and would not successfully be applied to a larger study area. Due to the limitations inherent in this fundamentally correlative approach, any interpretation of model results must refrain from making any definite causal relationships between any of the environmental variables and the vegetation classifications.

While classification trees are limited in their ability to explain causal relationships between environmental parameters and vegetation responses, they are also limited by the presumption that vegetation is assumed to be in equilibrium or quasi-equilibrium with its environment. Within the broader scope of the ecological modeling literature, the term "static" has been applied to describe this characteristic. Static models constitute a subclass of ecological models, of which classification trees are members (Franklin 1995). Static models are described as such because of their inability to account for the

dynamic nature of vegetation response to disturbances or environmental changes. The equilibrium concept has been widely debated in plant ecology, and criticized by many for its inability to acknowledge the ever-present nature of disturbances and other processes that are arguably ongoing natural components of virtually all ecosystems (Sprugel 1991). Despite its limitations as a theoretical construct, it is acceptable in predictive vegetation mapping to make the assumption of equilibrium or quasi-equilibrium especially at large spatial scales of analysis where incorporating disturbances and other more site-specific processes is logistically unrealistic (Cramer and Leemans 1993). Guisan & Zimmerman (2000) validate this in their claim that generally, "if high predictive precision is required to model the distribution of biological entities on a large spatial scale under present environmental conditions, then static modeling is a valid and powerful approach".

As with any geographic problem, the development of a research design and interpretation of results involve consideration of the issue of scale: "The form and composition of the biophysical landscape is a result of a composite of interacting processes that operate across a range of ...spatial and temporal scales… [where] relationships observed at a single spatial scale are not generalizable across all spatial scales" (Allen et al. 2004). Multiple patterns of vegetation result from processes shaping vegetation at different scales. A development of research design and interpretation for this study involved careful consideration of the ecological processes that determine vegetation patterns at various spatial scales. Climatic factors are thought to be

responsible for vegetation patterns at broader scales of inquiry (Sætersdal & Birks 1997), whereas geologic characteristics and species interactions, such as competition, predation, or symbiosis, are better predicted at fine scales than at more aggregate scales of analysis (Cairns 2001). An example of this phenomenon is that when incorporating only climatic environmental variables in a predictive model, geographic range distributions at the individual species scale of study are generally overestimated (Gioia & Pigott 2000). Given the regional spatial scale of this study, tradeoffs are introduced such that some loss of predictive capability of certain finer-scale processes result. Due to the exclusion of processes operating at finer scales, the model will predict vegetation patterns that are controlled by processes operating at the regional scale more accurately than it will predict vegetation patterns that are more dependent on finer-scale processes. Because of this limitation, the results from regional-scale studies will likely depict vegetation patterns resulting from climatic factors more readily than patterns resulting from processes such as geologic factors or competition and herbivory.

Another limiting factor in the application of PVM is the availability of suitable datasets. Due to this limitation, only selected factors that are both available, and considered to be important ecologically, are used in this study. Examples of datasets that are generally very scarce are historical land use changes and disturbances. These inter-related factors are difficult to quantify. An additional factor that has been little investigated using PVM, but nevertheless shown to play an enormous role in vegetation dynamics is the dispersal abilities of different species (Duckworth et al. 2000, Waldron, 2002), a factor

that is largely stochastic in nature. Given the lack of data for and potentially confounding effects of these variables, most PVM studies do not explicitly take these factors into account.

DEVELOPMENT OF DATA AND MODELS

In order to represent three levels of physiognomic aggregation of the vegetation, three separate classification tree models were developed using S-plus 6.1® statistical software (Insightful, Seattle, WA). Each model represents a different level of physiognomic aggregation of vegetation. All three of the models incorporate the same set of environmental layers as independent variables, but the vegetation is divided into a differing number of groups for each model. The first classification model (hereafter referred to as Model 1) incorporated all of the vegetation community types, representing the most specific classification of vegetation, and was not aggregated. Model 2 consists of a smaller number of categories of vegetation communities, and is aggregated to represent a higher level of compositional organization. Similarly, Model 3 contains even fewer categories of communities, and even more aggregation of vegetation. This model is the least descriptive floristically. The three models will be discussed in greater detail later.

The maps of vegetation used for the dependent variables in the three models were

supplied by the Swedish Surveying Agency, or "Lantmäteriet". The maps are at a scale of 1:100,000 and consist of 23 digital datasets classifying vegetation community types along the Swedish mountain area. The maps were produced by the Natural Geography Department at Stockholm University between 1978 and 1983 from aerial photographs taken between 1975 and 1982 (Esseen 2004). The dataset is the most up-to-date of its kind. The aerial photographs were taken in east-west transects from 9600 m altitude, yielding a scale on the negatives of about 1:60,000. Each of the 23 vegetation maps was interpreted, field checked, and adjusted by an interpreter. The field validation concentrated on areas that were difficult to interpret as well as on botanically interesting or unusual areas. Areas of more unusual vegetation types are likely somewhat underrepresented due to the methods used to classify the vegetation. Resolution of the data does not exceed 250 x 250 m to 300 x 300 m, or 6-9 ha, and no continuous tests of precision were made. Accuracy tests of the classification system revealed percent precision for main vegetation types of around 91%, varying between 80-98%, and 82% for less abundant types, varying between 70-89%. Systematic differences between interpreters with regard to the level of detail exist, as well as some problems with regard to areas transitioning into other types leading to inconsistencies in the dataset, as in for example between heaths dominated by woody plants and heaths dominated by graminoids. Table 1 lists the vegetation communities occurring within the study area along with a short description of some of the types regarding the dominant species.

For all three models, a stratified random sampling scheme was chosen to sample the data

Table 1. Vegetation map of the Swedish mountains describing vegetation community types occurring within the study area (Moen, pers. comm.).

VEGETATION TYPE	DESCRIPTION
Substrate dominated	
Boulder fields and exposed bedrock	Blocky areas and bedrock outcrops; few species, single individuals
Water	
Glacier	
Heaths	
Grass heath	Sparse vegetation dominated by *Carex bigelowii* and *Juncus trifidus*; in lower elevations other grass species may dominate; the vegetation type may turn into herb meadows at highly productive sites
Extremely dry heath	Low, mat-forming or creeping shrubs such as *Loiseleuria procumbens* and *Arctoptaphylos alpinus*, which forms patches; lichens are usually present but mainly found on wind-exposed ridges
Dry heath	Dominated by low shrubs such as *Vaccinium myrtillus*, *Empetrum hermaphroditum*, and *Betula nana*; very common vegetation type
Fresh heath	Larger shrubs due to better protection from snow, such as taller *Betula nana*, species of *Salix* and juniper
Wet heath	Heterogenous, patchy, tussocky vegetation; a mix of fresh heath patches and small mires
Meadows	
Low herb meadows	Grass and herb dominated vegetation; often associated with snow beds and microtine herbivory; may be very species rich in calcareous areas
Tall herb meadows	Very high productivity due to moving ground water (slopes in or near the birch forest with easily weathered rocks); tall herbs (1-2.5 m)
Meadows	No information given

Table 1. Continued.

VEGETATION TYPE	DESCRIPTION
Cultivated grounds and pastures	No information given
Snowbed vegetation	
Moderate snowbeds	Melts out every year; contains low shrubs such as *Salix herbacea*
Extreme snowbeds	Does not melt out every year; mostly mosses
Bogs and mires	
Bog and fen hummock vegetation	Hummocks with dwarf shrubs interlaced with *Sphagnum* mosses; grades into wet heath type
Bog with mud-bottoms and water-filled pools	>50% of the surface is wet muddy pools; the rest is composed of various mosses
Dry fen	Mires dominated by various *Carex* and *Scirpus* species (and other *Cyperaceae*); this is the most common mire in the mountains; usually fairly easy to walk in
Sloping fen	Similar to dry fen but with slopes usually around 5 degrees; located in very wet areas of the mountains
Wet fen	Very difficult to walk in; mosaic of wet and very wet patches, often associated with lakes
Mosaic mire	Mix of bog and fen hummock vegetation and dry fen
Various unusual mires	No information given
Shrublands	
Willow	Thickets of *Salix*; can be extremely dense and impossible to penetrate in areas
Deciduous shrubs	No information given
Deciduous forests	
Birch forest with lichens	Heath type; field layer with lichens and low dwarf shrubs; located in continental, dry areas
Birch forest with mosses	The most common birch forest with *Vaccinium* species, *Epetrum*, grasses, low herbs; sometimes a lot of juniper

Table 1. Continued.

VEGETATION TYPE	DESCRIPTION
Wet deciduous forest	No information given
Coniferous forests	
Coniferous forest with lichens	No information given
Coniferous forest with mosses	No information given
Coniferous forest with tall herbs	No information given
Various other types of coniferous forest	No information given
Other	
Settlements	No information given
Exploited areas	No information given

within the study area. It is advisable to use this type of sampling scheme "when the study area is large or relatively well known and covered by detailed maps and/or aerial photographs, and when physiographic distinctions are clearly delineated such that sampling can be stratified in accordance with them" (Allen et al. 2004). Stratified random sampling was used in order to ensure that all vegetation types were represented in equal proportions. Areas that were classified as "substrate-dominated", cultivated grounds and pastures, and "other" types of land uses that were classified as something other than vegetation were not sampled.

Categories falling within the realm of "substrate-dominated" types include boulder fields and exposed bedrock, water, and glaciers. These three categories were removed from

consideration in the model because no significant vegetation is indicated to be growing within these areas. The category of cultivated grounds and pastures, if vegetated, does not contain naturally-occurring vegetation and therefore does not lend itself to predictive modeling of naturally-occurring vegetation types. Similarly, the two categories falling within the "other" type– settlements and exploited areas– were not included because these areas were classified as a land use that does not contain naturally-occurring vegetation.

For each vegetation community type that was included in the models, a sample size of 1,000 points falling within the particular vegetation type was chosen. This size was chosen because it corresponds to near the maximum of sampling points containing unique attributes that could conceivably be sampled from vegetation types that are limited to a relatively small geographic area. To be more precise, in certain areas it was found that a sample size much larger than 1,000 points would introduce a problem where more than one point fell within a single cell of the DEMs. This problem was deliberately avoided by deleting points that happened to fall within the same cell of the DEMs for the 1,000 randomly selected points of each vegetation type. Because a large proportion of the environmental layers that were developed were developed from these DEMs, it made sense to avoid biasing the sampled dataset by choosing points that would induce replication of attributes that were derived from the DEMs. For the specific conceptual framework employed in this study, a dataset that contains as many examples of unique occurrences of the dependent variable is preferable to one that contains

repetitive observations of phenomena, as the uniqueness of each point in geographic space is more representative of the full range of ecological diversity that is naturally occurring in the study area.

For each of the three models, two datasets were created– one to train the dataset and one to validate the model results. This modeling technique is known as cross-validation. The first classification model (hereafter referred to as Model 1) incorporated all of the vegetation community types as the dependent variables listed in Table 1, i.e. the data was not aggregated. Model 2 consists of aggregated vegetation communities to test whether the model is more accurate in predicting communities at a higher level of taxonomic organization. Similarly to Model 1, the dependent variables for Model 2 consisted of 1,000 sample points from each of the vegetation types in Table 1 (excluding the "substrate-dominated" and "other" categories). These points would then be combined into the boldfaced categories in Table 1. For example, for the boldfaced "Meadows" category, 1,000 points would be sampled from each of the three subcategories "Tall herb meadows", "Low herb meadows", and "Meadows", for a total of 3,000 sample points. Note that "Cultivated grounds and pastures" was not included for reasons mentioned previously. Thus Model 2 contained varying numbers of sample points for each of seven aggregated vegetation types: (1) heaths, (2) meadows, (3) snowbed vegetation, (4) bogs and mires, (5) shrublands, (6) deciduous forests, and (7) coniferous forests. In this way, the dependent variable is aggregated into a higher level of physiognomy. For the third model, the dependent variables were then aggregated

further to determine if an even higher level of physiognomic aggregation was able to be predicted better with the model. The third model contained only three categories of vegetation types: (1) forests, (2) shrublands, and (3) other. The "forest" category contained 1,000 points sampled from each of the eight forest categories shown in Table 1. Similarly, the "shrublands" category consisted of 1,000 points sampled from each of the two shrubland types. Finally, the "other" vegetation type consisted of 1,000 points sampled from each of the remaining vegetation types. Recall that the boldfaced "other" category in Table 1 is excluded from sampling due to reasons mentioned previously.

DEVELOPMENT OF ENVIRONMENTAL VARIABLES

Predictive modeling of vegetation involves choosing explanatory variables based on literature linking bioclimatic gradients to plant distributions (Franklin 1998). Guisan & Zimmerman (2000) highlight some general guidelines for how to go about choosing the independent variables in ecological models. For modeling areas of complex topography, the authors, borrowing from the terminology of Austin and Smith (1989), suggest that the use of *indirect* variables may yield better predictions, while for simulations at large spatial scales, it is advised that *direct* and *resource* gradients should be used. Because the study area is both topographically complex and geographically large in extent, indirect, direct, and resource gradients are all utilized. For each environmental variable

chosen, ecological significance is discussed, followed by a description of the computational methods describing how the variable was developed for the study area.

It is recognized that plant community composition and structure are affected by many factors. These factors include variability in natural resource conditions such as solar radiation, temperature, and moisture regimes (abiotic factors), interactions between other plants and organisms such as competition and herbivory (biotic factors), and processes that have affected the site in the past such as land use changes, disturbance, and succession (historical factors). In most PVM studies, and for this application, natural resource conditions, or abiotic factors, are considered rather than biotic or historical factors, due to the limitations involved in quantifying these other factors especially at the broad scale studied here. It is important to keep in mind, however, that these other factors are also underway. Natural resource conditions can be broken down into climatic, topographic, and edaphic conditions. Climate governs geographic patterns of solar energy and water distribution. This in turn affects vegetation composition and structure. The effects of climatic phenomena on vegetation patterns are most clearly visible at broader scales of analysis such as regional or global scales (Duckworth et al. 2000). Conversely, at finer, more local scales, factors such as topographic and edaphic characteristics, biotic interactions, historical land use changes and disturbance regimes may play important roles (Parker et al. 2001) by mediating, or in some cases even counteracting (Duckworth et al. 2000) the effects of the major climatic resource gradients.

For this study, selected climatic, topographic, and geologic variables were taken into consideration as important predictors of vegetation composition and structure. The decision as to which explanatory variables were incorporated into the model was based on literature revealing both general ecological relationships of significance to vegetation distribution and composition at large, as well as more specific relationships that are representative of or exhibited in the vegetation dynamics playing out within and in similar geographic locations to the study area.

There are three main types of studies that provide insight into these relationships. Firstly, in situ experimental studies were considered, where vegetation is observed or manipulated where it is located geographically to determine physiological constraints. Secondly, studies employing paleoecological evidence were investigated to aid in understanding the past responses of vegetation to environmental changes. Lastly, various investigations incorporating modeling efforts were used to gage which variables may be the most useful in showing significant explanatory power within the specific modeling framework that is used for the present study. All of these approaches are helpful in understanding how vegetation changes might occur in response to potential future climate changes. The results of the classification models will be interpreted for their ability to correctly identify the present distribution patterns of vegetation on the landscape, though the results could potentially be used further to predict vegetation patterns as a result of impending global climate changes.

The following environmental variables were used to formulate the model. Some variables are direct measurements of climatic, topographic, or edaphic phenomena, while others require some computational processing to incorporate the mediating effects of topographic factors on the availability of climatic or geologic phenomena (Parker et al. 2001), and are expressed as indices that serve as metrics, or proxies for representing the interacting effects of climatic, topographic, and geologic forces.

Temperature and Precipitation

Temperature and precipitation are often cited as two of the most important climatic variables controlling vegetation distribution, composition, and abundance. Temperature is considered the most important limiting factor for vegetation growth in high elevations, and indeed vegetation in the Scandinavian mountains is chiefly constrained by cool temperatures and the short growing season. In the summer, monthly mean temperatures in the mountains are about 10°C, decreasing from south to north and with rising altitude (Carlsson et al. 1999), while the growing season is between 100-130 days (Vedin 1995). Low temperatures affect vegetation by reducing rates of photosynthesis and slowing the rate of decomposition of detrital material, leading to slower turnover of soil nutrients (Carlsson et al. 1999). The distribution of Scots pine (*Pinus sylvestris*), a common species in Swedish coniferous forest stands, is controlled primarily by the lower limit of summer temperatures (Engelmark and Hytteborn 1999).

Precipitation in Sweden varies considerably. It is in large part characterized by an increase from South to North, but the Scandinavian mountain area is an exception to this rule. The mountains impose an orographic component to the precipitation regime that has a greater effect than latitude. In the Scandes mountains, precipitation is much greater than the rest of Sweden, particularly closer to the Norwegian border where moist air masses from the Atlantic ocean can drop more than 1500 mm of precipitation a year as they pass eastward over the mountain chain (Carlsson 1999). Small glaciers sometimes form at high altitudes as a consequence of the heavy snowfall (Sjörs 1999). In contrast, on the leeward (east) side of the mountains, precipitation can be as low as 300 mm per year. This marked orographic moisture gradient is evident in the distribution of meadow and heath communities, which are more common on the western side of the mountains (Carlsson 1999). Precipitation also generally increases with altitude. In addition to geographic differences in precipitation, temporal (seasonal) variations also occur. Rainfall is lower in Spring and early Summer, and increases in July and August and into Autumn, during which more westerly areas in the mountains can be very wet, receiving as much as 100-130 mm of precipitation a month (Alexandersson & Andersson 1995). However, rainfall can vary greatly from year to year, and long dry periods have been experienced.

Direct measurements of temperature and precipitation were available for the study area from the National Atlas of Sweden digital datasets. The specific layers used include mean monthly measured temperature values for each of the 12 months, measured annual

precipitation, and actual annual precipitation. Temperature and precipitation data were gathered over the course of 30 years from 1961-1990 (Vedin 1995, Alexandersson & Andersson 1995). Temperature values are based on measurements taken at a fixed height above the ground at weather stations scattered within the study area, and are somewhat simplified due to the complex topographic influences (Vedin 1995). Measured annual precipitation values are based on manual measurement from gauging stations situated in and within close proximity to the study area. Actual annual precipitation is based on measurements from the stations, which are then corrected for errors introduced by wind, evaporation, and adhesion of precipitation to the instrument used to collect it. Both measured and actual precipitation values were analyzed manually following measurement. Because precipitation is difficult to analyze and highly variable in the study area, it is difficult to quantify, especially at the scale of the available maps. In addition, the time period in which the data was gathered is arguably too short to generalize the values to other time periods, due to large fluctuations in precipitation patterns in Sweden through time (Alexandersson & Andersson 1995). Mean monthly precipitation values were not available for the study area.

Evapotranspiration

Evapotranspiration is a measure of the availability of moisture for vegetation. Interestingly, the affect of evapotranspiration on water balance at any particular site is

not the same as the affects of other determinants of water balance such as depth to the water table, and so it is important to include evapotranspiration as a separate predictor variable in correlative modeling (Stephenson 1998). Evaporation of course varies over time and according to location, as more northern locations and higher altitudes experience a shorter warm period and thus less evapotranspiration than southerly locations and lower altitudes. The lower rates of evapotranspiration in these areas contribute to higher moisture availability for vegetation. Actual annual evapotranspiration data was available in the National Atlas of Sweden dataset. It includes both direct evaporation from the ground, wet plants, water, snow, and ice, as well as plant transpiration (Bringfelt & Forsman 1995).

First and Last Snow Day and Growing Season Length

The mountainous areas in Sweden are generally very wet. As mentioned, some areas can receive a great deal of precipitation, but this is not the only factor affecting the amount of moisture available for vegetation. While the surplus of water in some mountain areas is enhanced by higher precipitation and lower evapotranspiration rates, it is quite largely driven by snow melt in the spring, when many areas flood (Dahlström 1995). Because timing of snowmelt varies considerably across space and time, the surplus of soil moisture is highly variable (Sjörs 1999). A dataset indicating the timing of the first day with snow cover and the last day with snow cover (indicating time of

snowmelt) was available in the National Atlas of Sweden digital dataset. In the mountain areas, the first snow day generally occurs in early October, and the last snow day occurs between May or early June. This dataset was collected from measurements at weather stations within the study area. Satellite data provided ancillary information about the geographical distribution of snow (Dahlström 1995).

The length of the growing season influences the position, compositions, and organization of vegetation at the regional scale in alpine environments (Allen et al. 2004). One study noted that environmental predictors that are more physiologically based may yield more predictive power than those that are not (Prentice et al. 1992). Parameters quantifying "critical climatic thresholds that physiologically constrain the distribution of different vegetation life forms" are preferable to simple measurements of climatic parameters (Lenihan & Neilson 1993). Among other variables quantifying such parameters, growing season length was considered to be directly related to the survival, growth, and reproduction of plants in the aforementioned study. Growing season length was available in the National Atlas of Sweden dataset. It is defined as the number of days in the year that experience temperatures above +5 °C (Vedin 1995).

Maximum Snow Depth

Many species in Sweden vary along gradients representing winter conditions such as

surface water mobility, soil freezing, presence of local permafrost, and maximum snow depth. Oftentimes the depth of the snow is particularly important as a means of sheltering vegetation with a prostrate growth habit from inhospitable winter conditions (Engelmark & Hytteborn 1995).

Latitude

At the broadest scales, climate varies according to latitude. Both temperature and distribution of moisture vary by latitude. Range limits of forests have shifted along latitudinal gradients in Fennoscandia in response to climate changes occurring during the Holocene, and the range limits of *Betula pubescens spp. czerepanovii* in Northern Sweden have been particularly receptive to changes in climate (Sonesson & Hoogesteger 1983). In response to 20th century climate warming of 0.5°C and a 13% increase in precipitation, the range limits of *Betula pubescens* increased considerably, encompassing higher latitudes as well as shifting upward in altitude (Sonesson & Hoogesteger 1983). Sweden experiences considerable latitudinal differences in temperature during spring and autumn. Considering that the timing of many physiological processes in vegetation is largely dependent on climatic signals at the beginning and end of the growing season, it is not surprising to find that the vegetation in Sweden differs markedly following a latitudinal gradient. In general, coniferous forests are more prevalent in the southern part of the country, whereas deciduous mountain birch forests occur further north. As is

the case with most ecological relationships, species respond individualistically to a latitudinal gradient. Coniferous forests consisting largely of pine and spruce exemplify the differing responses of species to latitude, in that Scots pine trees grow in a significantly broader latitudinal range than Norway spruce trees (Engelmark & Hytteborn 1999). Latitude will thus likely prove to be an important explanatory variable, however it should be noted that in higher elevations the growing season is more dependent on local-scale snow conditions, where snow cover often acts to protect underlying vegetation during the winter months (Sjörs 1999).

Elevation, Slope, and Aspect

It is commonly understood based on much supporting evidence that vegetation is distributed across the landscape in elevational zones (Körner 2003). There is a marked elevational gradient in Sweden, and this gradient is as much or more important than the latitudinal gradient in the Scandes mountains (Sjörs 1999). One of the most dominant species of tree/shrub in Sweden, *Betula pubescens* spp. *czerepanovii,* commonly known as Mountain Birch, is distributed in such a manner, occurring primarily between 100 and approximately 300 meters a.s.l. (Sjörs 1999).

At first glance, it may be tempting to interpret elevation as the direct determinant of vegetation zonation, but one must take a closer look in order to understand how elevation fits within an ecological context. In particular, it is prudent to keep in mind

that it is not the differences in elevation per se that control vegetation distribution, but rather the mediating role that elevation plays in imposing gradients on major climatic factors (Turner et al. 2001), of which moisture regime and temperature are the most obvious. Precipitation generally increases with elevation, while temperature generally decreases by about 0.4ºC for every 100 meters of ascension in altitude (Carlsson, Karlsson, and Svensson 1999). In Sweden, there is a large decrease in temperature with increasing elevation particularly during the summertime (Sjörs 1999). *Betula pubescens* spp. *czerepanovii* is particularly sensitive to climatic changes including temperature, as in one study it was found that a 0.5°C increase in temperature and a 13% increase in precipitation during the 20th century has increased the altitudinal limit of Mountain Birch up to 50 meters (Sonesson and Hoogesteger 1983).

Insofar as elevation imposes ecological gradients on climatic factors, slope and aspect behave similarly by influencing microclimatic conditions. Slope is thought to play an important role in controlling soil moisture conditions by controlling soil formation and depth of soil, as well as modulating the depth to the water table and the rate of runoff. Aspect is thought to have a large influence on both floristic composition (Carlsson et al. 1999) and life-form of the vegetation (Armesto & Martínez 1978). In middle and high latitudes, differences in temperature and moisture availability due to aspect are very pronounced. In the Northern hemisphere, more southerly-facing slopes generally receive more solar radiation and hence higher temperatures than more northerly-facing slopes. Consequently, slopes with a southern exposure also tend to have drier soil

conditions due to higher potential evapotranspiration rates than those experienced on slopes facing north (Turner et al. 2001).

The implications of slope orientation for vegetation dynamics are often complex, may be species-specific, and dependent on site-specific factors. In alpine regions, some types of vegetation may favor southern exposures to capitalize on solar radiation absorption. An example of this favoritism in arctic/alpine regions is permafrost. Permafrost is present in areas of relatively high latitude. Where it is present, some vegetation types favor southern exposures instead of northern exposures because permafrost has been found to melt more extensively on more southerly-facing slopes (Bonan 1992). Because certain vegetation cannot grow well on permafrost, it will therefore be expected to select for south-facing slopes over north-facing slopes.

Of the environmental layers to be used in the model, elevation information was available directly from 50 meter resolution Digital Elevation Models (DEMs) covering the entire extent of the study area. These were obtained from the Swedish Surveying Agency, "Lantmäteriet" (Esseen 2004). Slope and aspect of each cell were derived from these original DEMs using standard algorithms in ArcGIS 9.0® (Environmental Systems Research Institute (ESRI), Redlands, CA) spatial analyst module, maintaining the same cell resolution of the original DEMs.

Geologic Substrate

Another environmental factor clearly shown to influence the distribution of vegetation is soil and its various characteristics. Detailed soil maps of the study area were not available to be included in the model, but substrate type was attained from the Swedish National Atlas (SNA) digital dataset (Fig. 2). It should be noted that although soil is generally derived from underlying parent material (i.e. bedrock), oftentimes it is overlain by other materials and only partially composed of this underlying material. This is sometimes the case in Sweden, where unconsolidated glacial deposits or fluvial sediments exist at the surface layer where vegetation grows (Sjörs 1999). Save the occasional presence of this overlying material, soils in the Scandinavian mountains are often composed only of the locally weathered material, and so bedrock is an important indicator of vegetation composition and physiognomy.

The characteristics of bedrock that are thought to be of importance to the composition and distribution of vegetation in Sweden are its degree of disposition to weathering and its calcium content, both of which are highly variable throughout the country (Sjörs 1999). About a third of the species of vegetation in the mountain area favor calcareous or other base-rich bedrock types, and 12% are calcium-dependent. In contrast, only 3% avoid these types and 50% show no preference one way or another (Sjörs 1999). The geologic substrate types within the SNA dataset consist of peat, clay-silt, sand-gravel,

glaciofluvial sediments, till, bedrock or thin cover on bedrock, till and weathered deposits above timberline, glaciers, and lakes.

Curvature

In a location where there is a considerable amount of topographic variability, such as in the mountainous environment of the study site, topography plays an important role in mediating the effects of certain resource gradients such as solar radiation, soil moisture potential, and soil nutrients. These resources in turn affect vegetation composition and structure. Curvature is one facet of topography that works this way in such environments. Areas that are more concave will collect more moisture and are more sheltered from radiation and mechanical stress such as wind, a factor that affects soil depth and consequently soil nutrients available for vegetation. Areas that are more convex tend to experience more runoff of water and consequently drier conditions, more exposure to radiation, though this in part depends on aspect, and less shelter from mechanical stress. Vegetation in Sweden such as mire vegetation is dependent on hydrological factors that are mediated by topography (Sjörs 1999).

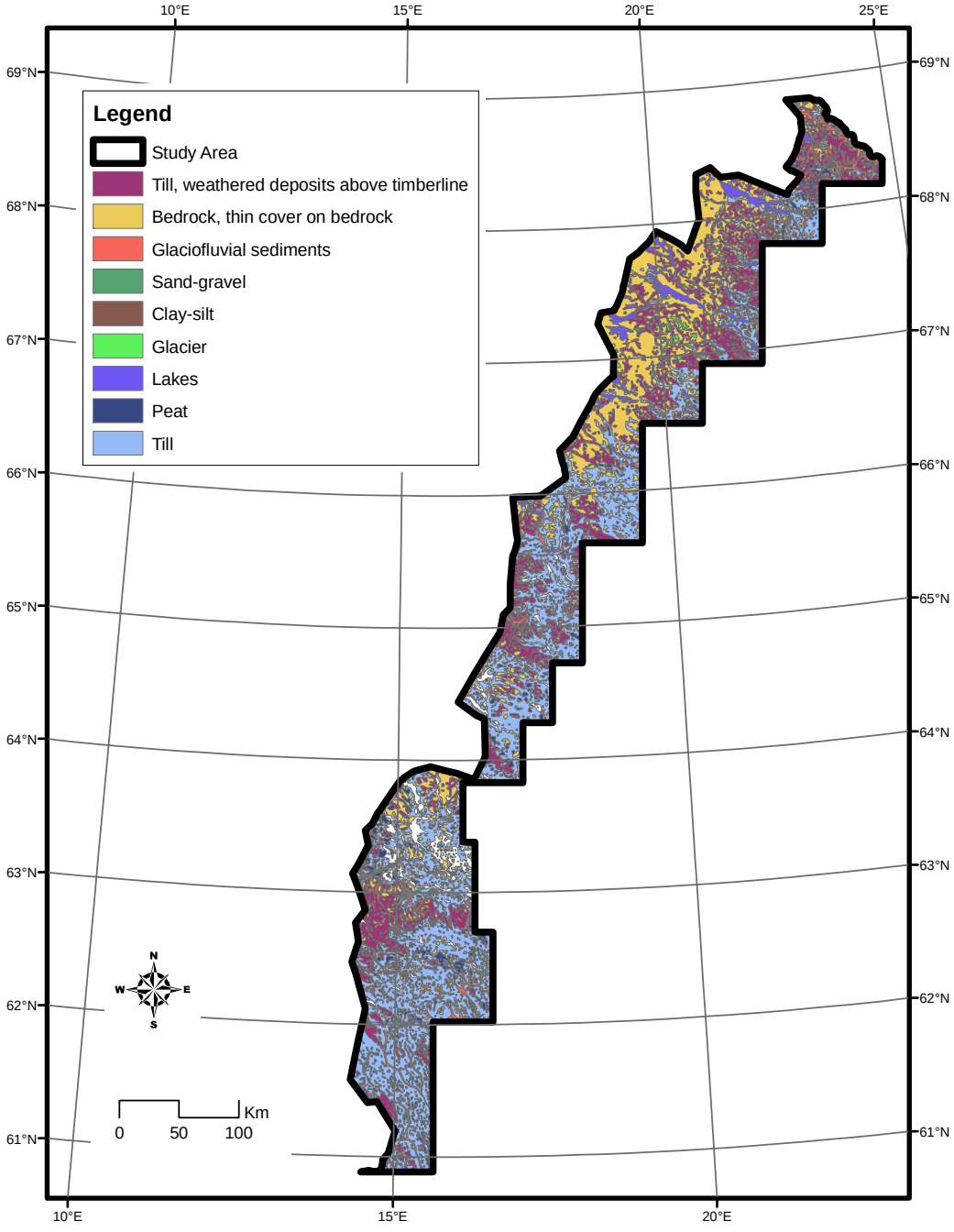

Fig. 2. Geologic substrate type within the study area.

Curvature was derived using a script written in Arc Macro Language (AML). The script utilizes the Grid module of ArcINFO (ESRI, Redlands, CA) to calculate a two-dimensional curvature value from the original DEMs on a cell-by-cell basis after Brown (1991). The first part of the formula involves calculating a one-dimensional curvature value using a 3 x 3 cell window surrounding the processing cell for four transects– a vertical transect, a horizontal transect, and two diagonal transects (Fig. 3). The equation for calculating one of these transects is as follows:

$$C_i = x_1 - 2x_2 + x_3 \quad (1)$$

where: x_1 = the first elevation value in each transect,

x_2 = the elevation of the point of interest, or the processing cell, and

x_3 = the third elevation value in each transect.

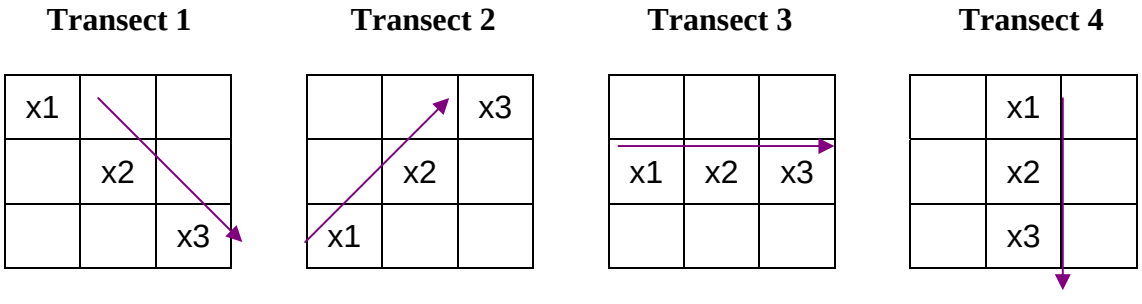

Fig. 3. Diagram illustrating method of calculating one-dimensional curvature for each of four transects.

The final two-dimensional curvature is then calculated by summing the one-dimensional curvatures of each of the four transects:

$$C = \sum_{i=1}^{4} C_i \quad (2)$$

where C = the two-dimensional curvature of the processing cell. Positive values of C indicate locations that are concave. Negative values indicate convex locations, and values of zero indicate a flat location. Once the curvature is derived following the above equations, the AML script scales the values of the curvature between -1 and 1 for ease of interpretation, such that +1 represents terrain that is highly concave, zero represents flat areas, and -1 represents areas that are highly convex.

Landforms

Because curvature takes into account only the grid cells immediately adjacent to the processing cell, it is not an adequate metric to capture broader scale terrain variability that indirectly influences vegetation distribution patterns. McNab (1993) developed a topographic index that takes this broader scale variability into account. Many processes

affecting vegetation productivity are related to landform- or meso-scale features in mountainous areas. Landform influences environmental characteristics of a site such as where precipitation is distributed geographically through subsurface flow, physical characteristics of soils, and characteristics of the atmosphere near the ground such as wind exposure (McNab 1979). These environmental characteristics influence height growth of vegetation as well as composition and distribution of tree communities. The landform index is based on topographic features that confine the observer's view of the horizon, and was derived by measuring the angle of the horizon from a stationary position using field equipment in the four cardinal directions, and then taking the mean of these four angles:

$$\text{Landform Index} = (x_1 + x_2 + x_3 + x_4) \ / \ (4 * 100) \quad (3)$$

where x = angle to the horizon, and the four subscripts represent the four cardinal directions North, South, East, and West in relation to the location of the observer.

Because it would be unrealistic to conduct field measurements from enough individual sites to accurately represent the complexity of all the landforms existing in an area as large as the study area, the index was instead adapted for use in a GIS. The calculation of the index was automated by writing a script in AML that derives the index from elevational information from DEMs. Due to computational limitations and limitations in the extent of the available DEMs, two important changes had to be made to the index.

These changes affected how the index was calculated, and because of these changes, the explanatory power of the index should be interpreted with caution. It is perhaps most instructive to begin by explaining how the index would theoretically be calculated under ideal conditions, followed by a discussion of the problems that were encountered in deriving the index computationally, how these problems were dealt with, and how the changes that were made to the index affected the subsequent interpretation of the index.

The index was derived by taking into account eight directions rather than four. It was thought that by considering eight directions, a more robust indication of the effect of landforms would be achieved. Taking this into consideration, ideally, the index would have been derived as follows. The angle to the horizon would be found by taking the arctangent of each cell in a DEM stretching in 8 directions far enough to capture the cell exhibiting the maximum angle between the elevation of the processing cell and the elevation of an unknown cell located an indeterminate distance away from the processing cell. The idea is that the angle of the horizon, or the angle of where landforms end and the sky begins, in one of the 8 directions, translates to the largest angle that could be found between any point in the DEM and every point extending to an unknown distance in that particular direction.

The most substantial problem encountered was one of processing power. The available computers used to conduct research could not process an area as large as the extent of one of the DEMs. Thus, the farthest distance from the processing cell that could be

considered in determining the maximum angle in each of the 8 directions was 35 cells. This corresponds to an actual distance of 1.75 kilometers on the ground, a distance which may or may not be great enough to capture the maximum angle. Despite this limitation, for each cell in the DEM, a maximum angle was found between the 35 cells able to be considered in each of the 8 directions, and the mean angle between these 8 directions was then calculated.

The second problem encountered in deriving the index was that of the discontinuous nature of the DEMs leading to "boundary issues". DEMs had to be processed individually due to the aforementioned problem with computational power. This limitation created a problem where the area of the DEM within 35 cells of the boundary of the DEM did not have 35 cells between the processing cell and the boundaries of the DEM to consider in determining the maximum angle. Consequently, within this area it was only possible to process the number of cells between the processing cell and the boundary of the DEM. This problem decreases the general accuracy of the index within a 35-cell area near the boundaries of each DEM. Also, within this area the accuracy decreases as the DEM boundaries are approached until the one-cell boundary cells are reached, at which point no processing was performed because the cells in at least one direction from the processing cell did not exist, and could therefore not be considered. These border cells were assigned NO DATA values.

Due to the above issues, the index should be interpreted with caution. The validity of the dataset could be criticized for not considering a large enough distance in each direction in calculating the maximum angles. Additionally, the values of the index in areas near the boundaries of the DEMs are suspect. In the future, if this method is used to derive the index, it will either have to be computed on a much more powerful computer that can handle very computationally-intensive processes, or the study area will have to be much smaller in order for existing computers to handle the derivation of the index. In the event that sufficiently powerful computers are available or the study area is smaller, one must also realize that even if a DEM can be processed that is large enough to seamlessly cover the entire study area, this DEM must ideally extend a considerable distance beyond the study area in all directions to successfully overcome the boundary issue.

Continentality

Differences in the rate of heating and cooling of water and land are responsible for a well known phenomenon affecting regional temperature patterns. Because land heats and cools faster than water, terrestrial areas that are farther from the ocean and less influenced by it tend to have a greater range between minimum and maximum temperatures, both daily and yearly, than maritime locations closer to the ocean (Turner et al. 2001). In addition to the moderating affect on temperatures, the proximity to the

Atlantic coast is a measure of the amount of precipitation received in the Scandes mountains. Not surprisingly, precipitation increases with closer proximity to the coast. Logically, any factors that affect temperature and precipitation patterns are going to subsequently affect the geography of vegetation, and vegetation corresponds to these gradients between maritime versus continental locations in some key ways. In Sweden, temperature is less variable closer to the Norwegian border than farther east (Sjörs 1999). Within the study area, it has been documented that there is a strong climatic West to East oceanic-continental gradient in the Abisko area of Northern Sweden (Karlsson & Callaghan 1996). The distribution of heath and meadow vegetation is thought to be largely influenced by distance to the coast, this type of vegetation favoring more western, oceanic areas (Carlsson, Karlsson, & Svensson 1999). Research shows that certain types of vegetation in Scandinavia do not grow in more westerly areas that have milder winters, because this causes premature growth and subsequent frost damage (Sætersdal & Birks 1997). It has also been found that conditions are more favorable for paludification, or the transition from forests to the formation of bogs, in wetter, more maritime climates such as Fennoscandia (Crawford, Jeffree, & Rees 2003, Sonesson & Hoogesteger 1983). Vegetation composition within bogs largely depends on the degree of oceanic/continental influence (Rydin, Sjörs, & Löfroth 1999). Certain other types of vegetation in the study area may also show a correlation to a gradient measuring the increased degree of continentality from west to east across the study area.

Climatic variability due to the degree of continentality can be expressed through a

surrogate variable consisting of the distance to the coastline. Distance from the coast was developed for the study area by running a spatial analysis of the Euclidean, or straight line, distance from the Norwegian coastline (Fig. 4) using ArcGIS (ESRI, Redlands, CA). In addition to this derived metric, the SNA contained a digital dataset representing continentality. This dataset was included as well as the derived metric for continentality, because it was calculated using different criteria than distance to the coastline. It was calculated instead based on seasonal and daily temperature fluctuations, with larger fluctuations indicating areas with a more continental climate. Specifically, it was calculated as the sum of the differences in temperature between July and January and between day and night in June (Vedin 1995). These two metrics may show similar predictive power, or may show differences, and so both were included to allow the model to choose which to use, if either.

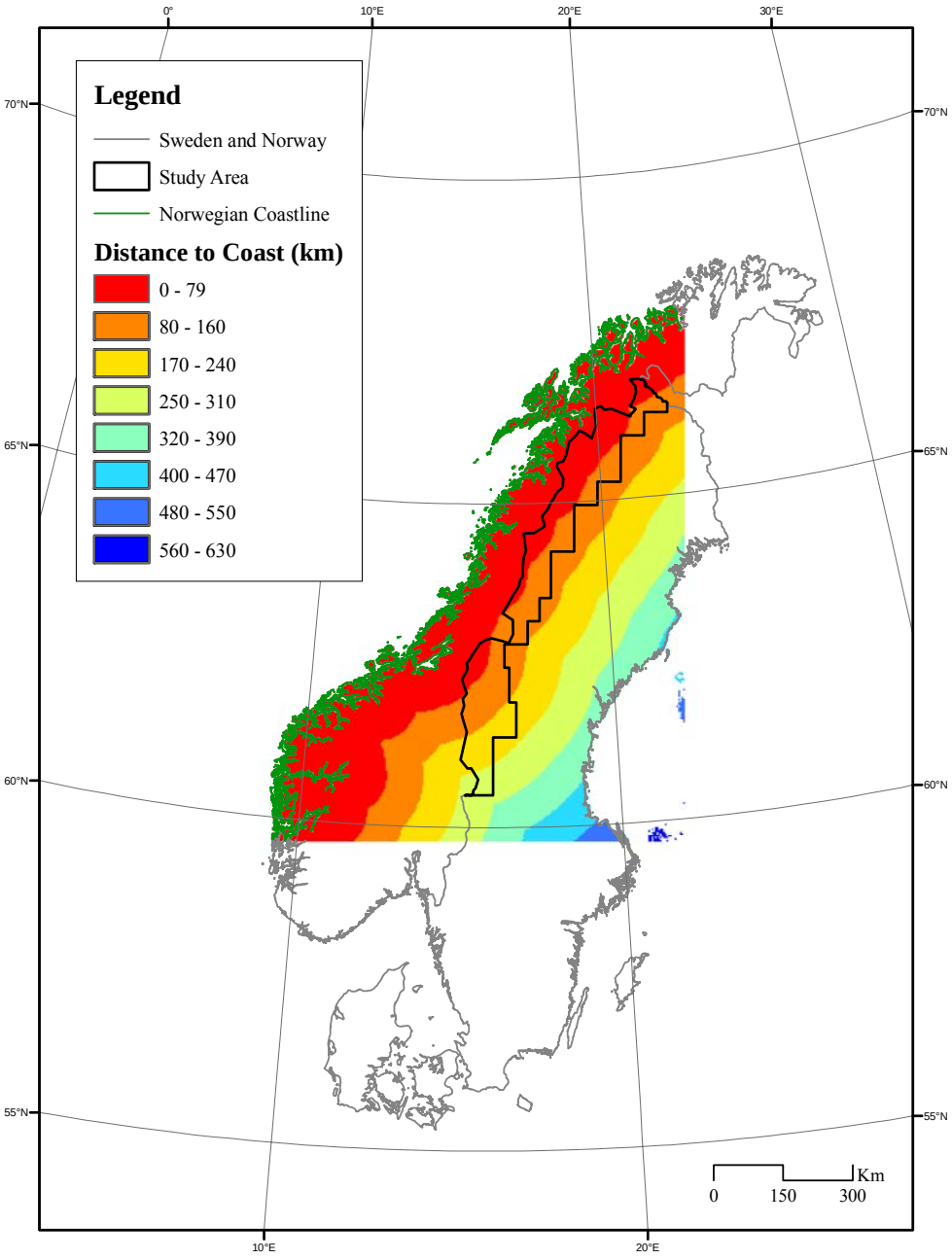

Fig. 4. Euclidean distance from the Norwegian coastline.

Solar Radiation and Cloud Cover

An important environmental variable that needs to be taken into consideration is solar radiation. There are several components to radiation. Direct radiation refers to the solar energy that strikes an object on the ground without having been dispersed by clouds through the atmosphere. Diffuse radiation is solar energy that is dispersed by clouds before striking features on the surface of the earth. Reflected radiation is solar energy that has been reflected off of the surface of the earth back onto other objects. Direct radiation is considered to be the largest component of radiation affecting vegetation, followed by diffuse radiation.

Latitude imposes a gradient on solar radiation across the surface of the earth, and at finer scales, topographic relief is the major factor modifying the distribution of insolation. "Variability in elevation, surface orientation (slope and aspect), and shadows cast by topographic features create strong local gradients of insolation" (Fu & Rich 2000). All of these factors cause a high degree of spatial and temporal heterogeneity in local energy and water budgets which in turn creates a variable microenvironment for vegetation. In this way, differential insolation patterns affect much more than just the availability of light for photosynthesis. Factors such as air and soil temperature regimes, evapotranspiration rates, snow melt patterns, and soil moisture are also affected. All of these are factors that affect vegetation distribution and composition. Evapotranspiration rates, snow melt patterns, and soil moisture are also affected. All of these are factors

that affect vegetation distribution and composition.

Many types of vegetation are shade-intolerant, and therefore do not readily grow in areas where light is obstructed by other vegetation or topography. This is the case with regard to *Betula pubescens* spp. *czerepanovii* (Nikolov and Helmisaari 1992). In the Abisko area of Northern Sweden, the effects of increases in UV-B radiation were studied in natural, dwarf shrub heaths, a vegetation type that represents a major component of arctic regions across the globe. It was found that the direction of responses were species-specific, but that negative responses were evident, indicating that some shrubs experienced reductions in shoot growth and earlier leaf senescence as a result of the elevation of radiation (Björn et al. 1997). It was also concluded that the negative responses could be more damaging over time. An analysis of the response of mosses, a vegetation type that is very important in sub-arctic vegetation in the study area, to elevated UV-B radiation and increased summer precipitation was also conducted in this study. Certain species of moss showed great increases in growth in response to the two variables in combination, however elevated radiation alone produced no effect or a decrease in growth on these species (Björn et al. 1997). While the physiological responses of vegetation in Sweden to radiation is often specific to vegetation type and may be dependent on the interaction with other variables, radiation is nonetheless a definite factor playing a role in vegetation composition and structure.

A metric was derived from a model of the solar radiation received within the study area by using an extension to ArcView 3.3 (ESRI, Redlands, CA) called Solar Analyst. The extension was developed by Helios Environmental Modeling Institute, LLC, Kansas, U.S.A (Fu & Rich 2000). This model takes into account both local topographic factors from DEMs as well as broader scale impacts of latitude due to the earth's revolution around the sun in calculating insolation values. For this study, three critical times during the year were considered– summer solstice, winter solstice, and the equinoxes. These three times give an indication of solar radiation values in mid-summer, mid-winter, and the intermediate periods of fall and spring (as radiation due to the earth's revolution is similar at the two equinoxes). The solar radiation amount (in watt hours per square meters (WH/m^2) and duration during these three periods may shed some light on the importance of seasonal patterns of insolation for various vegetation types. The Solar Analyst models global, direct, diffuse, and duration of radiation for the DEMs by taking into account the mediating role that topography plays in the availability of energy and water for vegetation. Global radiation is calculated as the sum of direct and diffuse radiation. Parameters were entered by the user to account for the effects of clouds. Specifically, the diffuse proportion was set to 0.4 indicating generally clear sky, and transmittivity was set to 0.4, also indicating generally clear sky. Refer to Figs. 5 and 6 for maps of direct radiation modeled at the summer solstice and at the autumnal equinox for the Abisko vegetation area. Note that the Abisko area was used to show modeled radiation instead of the entire study area, as this would be difficult to interpret visually due to the immensity of the study area. Also note that radiation values at the winter

solstice are excluded because the Abisko vegetation area is North of the arctic circle, and therefore does not receive any radiation at this time.

In addition to the Solar Analyst datasets for radiation duration, SNA datasets representing the duration of sunshine in June and December were also included. These datasets indicate the number of hours of sunshine occurring in the two months across Sweden (Josefsson 1995). June and December were chosen as the months to include because these months give an indication of what the radiation budget is like in mid-summer and mid-winter, the two temperature extremes experienced in the area. It is thought that in an area of such northerly position, vegetation may show a greater response to dramatic seasonal variations in radiation duration than to more subtle differences derived from annual mean values of this variable across space.

While solar radiation is known to play a significant role in vegetation distribution, it is not always able to reach the surface of the earth. Because clouds mediate the amount of solar radiation available for vegetation, they may play an even greater role in controlling vegetation patterns than radiation. Datasets for percent mean annual cloud cover, as well as percent mean seasonal cloud cover (in January and July) were available from the SNA (Andersson & Josefsson 1995), and were utilized as parameters in the model.

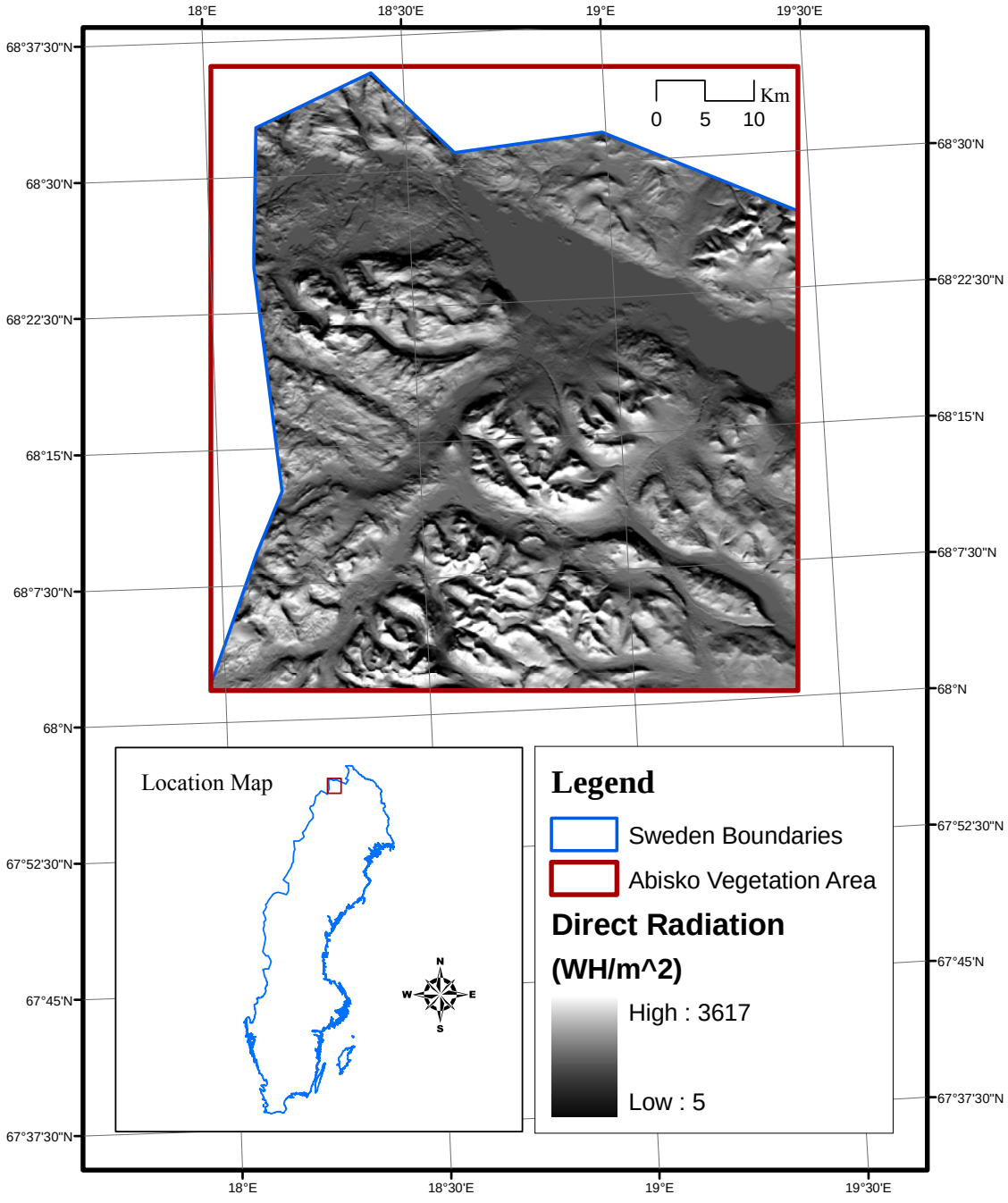

Fig. 5. Direct radiation at the summer solstice, modeled for the Abisko vegetation area, a portion of the study area in northwestern Sweden.

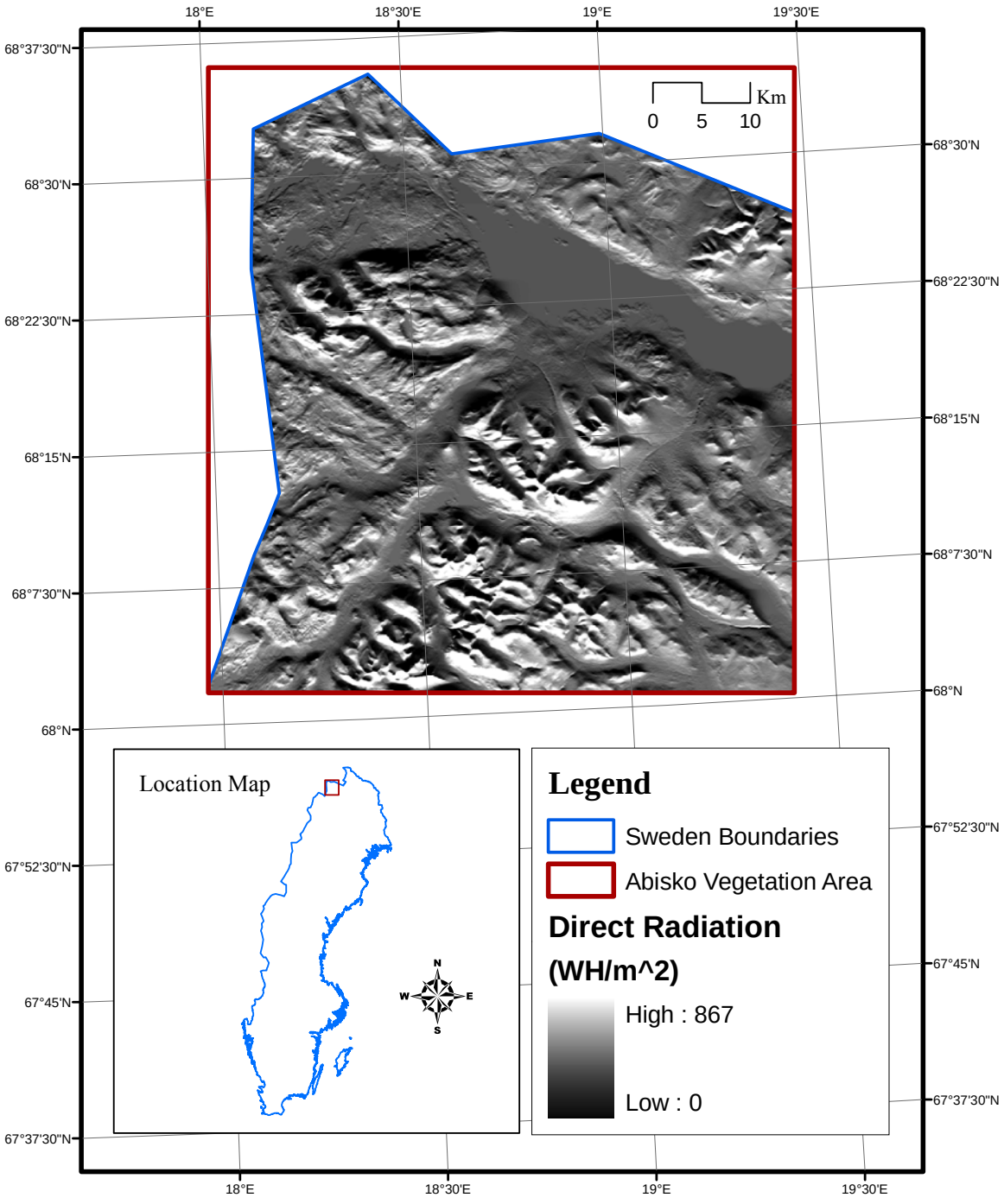

Fig. 6. Direct radiation at equinox, modeled for the Abisko vegetation area.

Soil Moisture

Like light availability, soil moisture plays a large role in the distribution of vegetation. In one study utilizing regression tree modeling, the spatial patterns of shrub abundance in California chaparral were found to be most strongly associated with annual soil moisture and average annual solar radiation (Meentemeyer et al. 2001). Due to differing physiological tolerances, some types of vegetation favor wetter soil conditions while others thrive in drier conditions. The coniferous forests in Sweden primarily respond to two main environmental gradients– those of soil moisture and soil nutrients, and the two gradients are inter-related (Engelmark and Hytteborn 1999). The species *Betula pubescens* spp. *czerepanovii* is known to grow on a range of soils, but does not appear to tolerate particularly dry conditions (Nikolov & Helmisaari 1992). In contrast, the most important limiting factor for the growth of vegetation in bogs, a common feature in Sweden, is excessive moisture.

Though soil moisture is considered a major determinant of vegetation distribution, composition, and structure, it is difficult to quantify. As discussed previously, soil moisture in Sweden is related to timing of snowmelt, because moisture is trapped during the winter months in snow and ice, and only becomes available for vegetation in spring when extensive melting occurs. Where soil moisture is particularly high, conditions are amenable to bog formation and peat-forming mires (Sjörs 1999), features that are common in northern and western Sweden. While soil moisture in Sweden is heavily

influenced by snowmelt, it is also affected by topographic factors. For this study an algorithm was chosen that derives a topographic wetness index after the work of Beven and Kirkby (1979). This hydrological model is physically-based and takes into account the contributing area to drainage basins:

$$\ln(a/\tan\beta) \quad (4)$$

where a = the area drained per unit contour length, and

β = local slope angle.

While this model has the advantage of integrating topographic data into the formulation of an index, it does not take into account seasonal factors affecting soil moisture in this area– namely the large influx of water at the time of snowmelt. A script written for implementation in ArcView 3.x of the topographic moisture index was attained from the ESRI web site (*http://www.esri.com*). A smoothing addend parameter was specified prior to running the script. The values of this parameter ranged between 1 and 100. A value of 1 emphasizes ridges in the terrain, and is recommended for areas of high relief. A value of 100 in essence "blurs" the ridges, and is recommended for areas of low relief. Parameter values of 1 and 100 were entered to produce the soil moisture maps (Figs. 7 and 8).

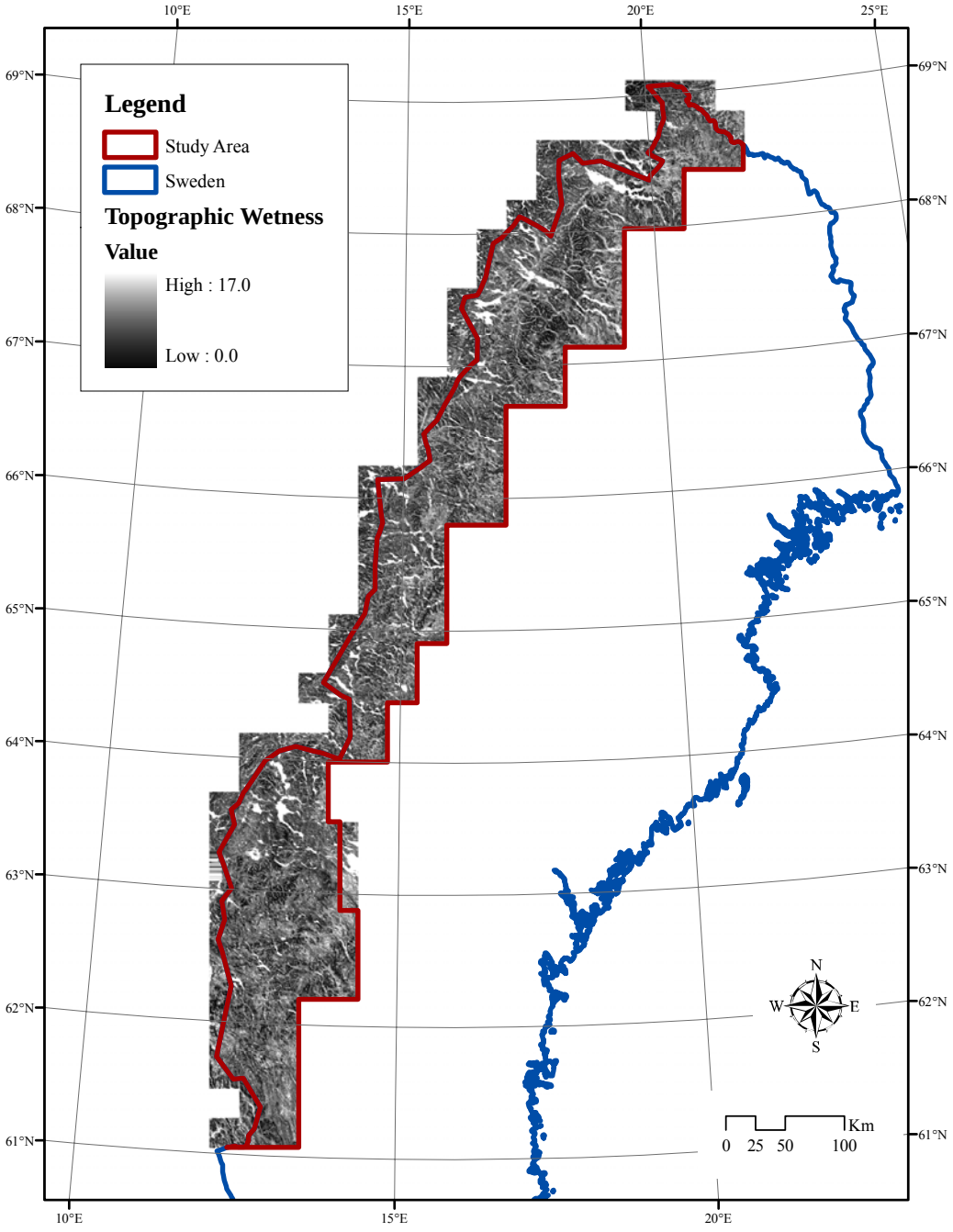

Fig. 7. Topographic wetness index, with smoothing addend = 1.

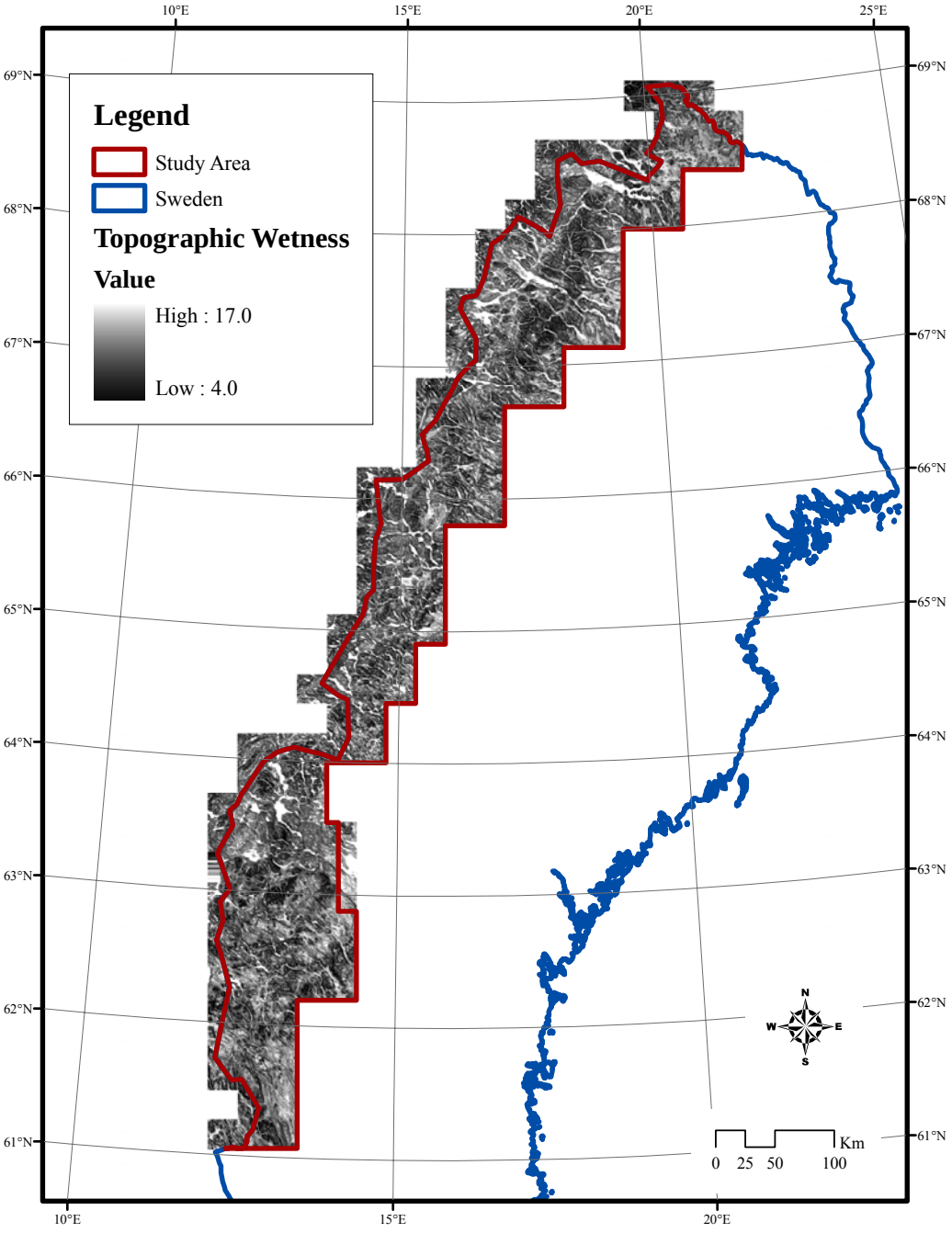

Fig. 8. Topographic wetness index, with smoothing addend = 100.

RESULTS AND DISCUSSION

Once the three models were run, pruned, and results were attained for each of the three models, several measures were derived to assess the performance of the models. Among these, an overall accuracy statistic was attained, as well as a kappa statistic. The kappa statistic has been widely employed in the predictive vegetation modeling literature as a useful measure of accuracy for this type of model (Congalton, Oderwald, & Mead 1983, Congalton 1991). Furthermore, confusion matrices for each of the three models were created, indicating the proportion of sample points that were predicted as the correct vegetation type, as well as the proportion of sample points that were predicted as each of the other types of vegetation. Additionally, individual accuracy statistics were created that show how accurate each model was at predicting each category of vegetation. The predictor variables that were used in each of the three models are listed in Table 2. Note that not all of the environmental predictor variables were utilized by any of the three models. Overall accuracies and kappa statistics for all three models are shown in Table 3. More detailed discussion of the individual results of each model follow.

Once the results were obtained and accuracies assessed for the study area as a whole for the three model frameworks, the three models were then applied to a smaller region within the study area— the Abisko vegetation area— in order to visualize spatial patterns at a finer, more meaningful scale. The Abisko area resides in the northern region of the study area. Maps of the predicted vegetation types were created for each of

the three models. These results indicate that the classification model does better at predicting vegetation types at higher levels of aggregation of the dependent variable. For instance, the model is better at predicting the presence of forests than it is at predicting the exact type of forest (for example birch forest with lichens). This finding is not surprising given that at higher levels of aggregation of vegetation, there are fewer categories of vegetation to predict, and the model therefore does not have to differentiate between as many specific floristic components. With increasing aggregation of composition, specificity of vegetation composition is relaxed, allowing the model leeway to be more generalized in its predictions.

The overall accuracies of the three models is illustrated in Table 3. Due to the low accuracy of Model 1 shown in this table, it is clear that few of the vegetation types are correctly predicted. However, referring to Table 3, Models 2 and 3 show increased accuracy.

MODEL 1

Recall that Model 1 included all of the available vegetation types as dependent variables. In other words, the vegetation data was not aggregated at all. The classification tree, or the "dendrogram", produced by Model 1, is illustrated in Figures 9A-E. The overall accuracy of this model (Table 3) indicates that this model correctly classified vegetation

Table 2. Environmental variables used in each of the three models.

Variables	Description	Units	Model 1	Model 2	Model 3
elevation		meters	√	√	√
slope		degrees	√	√	√
aspect		degrees	√	√	
curvature		unitless			√
mcNab	Landform Index	unitless		√	
wet1	Topographic Wetness Index, with smoothing addend = 1	unitless	√	√	√
wet100	Topographic Wetness Index, with smoothing addend = 100	unitless	√	√	√
distance to coast		kilometers	√	√	√
dir summer	direct radiation	wattHrs/m^2			
dir equinox	direct radiation	wattHrs/m^2			√
dir winter	direct radiation	wattHrs/m^2			
dif summer	diffuse radiation	wattHrs/m^2	√	√	√
dif equinox	diffuse radiation	wattHrs/m^2	√	√	√
dif winter	diffuse radiation	wattHrs/m^2			
glb summer	global radiation	wattHrs/m^2	√	√	√
glb equinox	global radiation	wattHrs/m^2		√	√
glb winter	global radiation	wattHrs/m^2			
dur summer	duration radiation	hours/day	√	√	
dur equinox	duration radiation	hours/day		√	√
dur winter	duration radiation	hours/day			
Geology	a: bedrock b: clay-silt c: glacier		√	√	√
	d: glaciofluvial sediments e. lakes				
	f: peat g: sand-gravel h: till				
	i: weathered sediments above timberline				
percent precip snow		%	√		√
Mean cloud cover jan		%			√
Mean cloud cover july		%	√	√	
Mean annual cloud cover		%			
Mean temp jan		°C	√		
Mean temp feb		°C			√
Mean temp mar		°C	√	√	

Table 2. Continued.

Variables	Description	Units	Model 1	Model 2	Model 3
Mean temp apr		°C	√	√	√
Mean temp may		°C			
Mean temp jun		°C		√	√
Mean temp jul		°C			√
Mean temp aug		°C			
Mean temp sep		°C		√	√
Mean temp oct		°C	√	√	
Mean temp nov		°C			√
Mean temp dec		°C	√	√	√
last snow day	c: Oct 15 d: Oct 20 e: Oct 25		√	√	
first snow day	c: Oct 15 d: Oct 20 e: Oct 25		√	√	√
growing season length		days	√	√	√
max snow depth		cm			√
Latitude		°North	√	√	√
continentality		°C			
annual precip		mm			√
annual evaporation		mm			
Sunny days june		unitless			√
Sunny days dec		unitless	√		
measured annual precip		mm		√	

Table 3. Overall accuracies for the three models.

Model #	Accuracy	Kappa
1	0.358	0.334
2	0.538	0.461
3	0.712	0.569

only 35.8% of the time. A common way to illustrate the predictive capabilities of classification trees is using a confusion matrix. Confusion matrices show for each vegetation type the percentage of observations in which the correct vegetation types are predicted, as well as the percentages for incorrect prediction of observations as each of all of the other types of vegetation. Results of Model 1 (Table 4) showed particularly strong predictive capability for extreme snowbed vegetation, deciduous shrubs, bogs with mud bottoms, and tall herb meadows. In contrast, Model 1 showed quite weak predictive capability for dry heaths, fresh heaths, willow shrubs, and wet fens. Other vegetation types fell within the mid-range of predictive capability. Individual accuracy statistics are shown in Table 5, followed by a predicted vegetation map produced by applying Model 1 to the smaller vegetation area of Abisko (Fig. 10) Note that there are large areas in the maps indicating no data. These are areas classified as one of the categories mentioned previously that were excluded from the analysis: boulders & exposed bedrock, glaciers, water, cultivated areas, settlements, and exploited areas.

Table 4. Confusion matrix for Model 1. Correctly predicted vegetation types are in bold.

Predicted Veg.	birch forest lichens	birch forest mosses	birch forest tallherbs	bog fen hummock	bog mudbottoms	conif forest lichens	conif forest mosses	conif forest tallherbs	decid shrubs	dry fen	dry heath	extreme snowbeds	extremely dry heath	fresh heath	grass heath	low herb meadows	meadows	moderate snowbeds	mosaic mire	sloping fen	tall herb meadows	var conif forest	var unusual mires	wet decid forest	wet fen	wet heath	willow shrubs
Actual Vegetation																											
birch forest lichens	**52.2**	1.6	1.2	0.6	2.8	8.0	0.0	0.2	0.2	0.6	0.8	0.0	0.0	0.0	0.0	0.0	2.2	0.0	8.8	1.4	1.8	0.2	2.2	6.0	0.0	8.2	1.0
birch forest mosses	7.2	**17.2**	13.6	1.8	0.4	7.8	1.6	3.2	0.6	2.4	2.2	0.6	0.2	1.6	0.4	0.4	3.6	0.0	13.8	4.2	3.6	0.2	0.8	1.0	0.0	8.6	3.0
birch forest tallherbs	0.8	9.2	**27.6**	2.6	1.8	3.6	2.2	11.0	0.4	0.8	0.2	0.6	0.0	2.2	0.4	1.6	3.8	0.0	2.8	5.0	16.0	0.0	0.4	0.6	1.2	2.8	2.4
bog fen hummock	5.0	1.4	2.2	**17.8**	6.8	15.8	4.4	6.8	0.0	2.2	0.0	0.0	0.4	0.4	0.2	0.0	4.2	0.2	19.6	2.2	0.0	0.0	0.8	0.0	6.8	2.8	0.0
bog mudbottoms	0.4	0.0	0.0	7.8	**69.8**	8.6	0.6	3.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	2.4	0.0	1.0	0.0	0.0	0.0	0.0	0.0	4.8	1.4	0.0
conif forest lichens	2.8	1.8	0.4	4.2	2.6	**61.4**	8.4	7.4	0.2	0.6	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	2.4	0.0	1.0	0.0	0.8	0.0	1.4	0.6	0.0
conif forest mosses	1.2	3.4	3.4	2.8	2.6	22.2	**26.8**	20.4	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	7.6	0.0	5.0	0.4	0.2	0.0	0.0	0.0	2.2	0.6	0.2
conif forest tallherbs	0.0	0.8	9.0	0.4	1.0	4.6	9.2	**51.8**	0.2	0.4	0.0	0.0	0.0	0.0	0.0	0.0	9.8	0.0	3.6	4.2	0.6	0.0	0.0	0.0	4.4	0.0	0.0
decid shrubs	11.4	0.0	0.0	0.0	0.4	0.2	0.0	0.0	**71.6**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	3.8	10.0	2.0	0.0	0.0	0.0
dry fen	2.8	2.2	3.2	3.8	1.0	5.4	2.0	5.8	0.2	**11.2**	0.4	0.2	1.4	5.0	5.4	1.6	1.4	0.8	19.0	6.6	0.4	0.0	0.0	0.0	5.4	14.2	0.6
dry heath	6.8	1.6	3.6	0.0	1.0	2.6	0.0	0.8	1.6	6.6	**4.0**	7.0	10.6	2.8	4.0	8.2	0.0	4.6	4.0	2.8	4.6	0.0	1.4	2.4	0.4	13.8	4.8
extreme snowbeds	0.0	0.8	0.8	0.0	0.4	0.2	0.0	0.0	0.0	0.6	0.0	**75.0**	4.8	0.0	2.8	7.4	0.0	2.8	0.0	0.0	2.8	0.0	0.0	0.0	0.0	0.8	0.8
extremely dry heath	8.6	1.6	1.6	0.8	0.2	1.4	0.0	0.2	0.0	3.8	4.8	12.2	**20.2**	0.8	6.2	8.6	0.0	4.2	2.2	2.0	3.2	0.0	0.0	0.2	0.0	12.0	5.2
fresh heath	4.6	2.8	7.6	0.8	0.6	1.0	0.2	1.0	1.0	6.8	3.0	1.6	4.6	**8.0**	1.6	6.8	0.0	0.4	7.2	5.4	7.0	0.0	1.4	2.8	0.6	15.0	8.2
grass heath	0.8	0.4	0.0	0.0	0.4	0.4	0.0	0.0	1.6	1.8	1.6	34.8	7.8	0.0	**15.2**	3.6	0.0	16.2	0.2	1.0	3.6	0.0	0.0	0.8	0.0	7.8	2.0
low herb meadows	0.2	0.4	3.2	0.0	0.4	0.0	0.2	0.4	0.0	3.0	1.0	23.2	9.2	1.0	4.0	**19.6**	0.0	15.0	0.2	1.2	12.4	0.0	0.0	0.0	0.0	4.0	1.4
meadows	0.8	0.6	4.8	6.6	1.0	10.4	14.4	7.8	0.2	0.8	0.0	0.0	0.0	0.4	0.0	0.0	**44.4**	0.0	3.0	0.6	0.4	0.0	0.2	0.0	3.4	0.2	0.0
moderate snowbeds	0.0	0.6	0.6	0.0	0.4	0.2	0.0	0.4	0.4	1.4	0.0	30.8	5.2	0.0	4.0	9.4	0.0	**38.0**	0.0	0.8	3.8	0.0	0.0	0.0	0.0	2.8	1.2
mosaic mire	7.4	0.4	1.0	5.8	2.2	8.4	3.4	5.8	0.2	2.2	0.0	0.0	0.2	0.6	0.0	0.0	2.4	0.0	**40.0**	7.2	0.2	0.0	0.4	0.2	6.4	5.2	0.4
sloping fen	1.4	3.4	7.0	2.2	0.6	1.4	4.8	27.8	0.2	6.2	0.4	0.4	0.8	1.0	0.6	0.8	2.8	0.0	9.8	**11.6**	1.6	0.0	0.0	0.0	8.0	6.8	0.4
tall herb meadows	0.0	1.6	5.2	0.0	0.6	0.2	0.0	0.4	0.0	1.0	0.0	8.6	0.8	0.8	0.2	9.8	0.0	0.2	0.4	0.4	**65.6**	0.0	0.0	0.0	0.0	1.4	2.8
var conif forest	3.4	0.0	0.0	0.0	3.0	1.0	0.0	0.0	2.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**47.2**	31.4	11.4	0.0	0.2	0.0
var unusual mires	2.6	0.0	0.0	0.0	5.0	0.4	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.0	**61.6**	22.8	0.0	0.0	0.0
wet decid forest	0.2	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	13.6	32.0	**50.2**	0.0	0.0	0.0
wet fen	6.8	0.4	0.6	8.2	3.8	7.4	0.4	2.4	0.0	4.6	0.2	0.2	1.0	0.4	3.2	0.0	2.2	0.4	25.6	1.8	0.4	0.0	0.2	0.0	**9.6**	20.0	0.2
wet heath	9.0	3.6	2.2	0.8	0.0	1.8	0.0	0.6	1.4	3.8	3.8	0.4	3.6	4.4	1.4	1.4	0.0	0.2	6.8	4.8	2.6	0.4	2.0	1.8	0.0	**41.0**	2.2
willow shrubs	6.6	2.2	3.8	0.6	0.6	1.0	0.0	0.0	0.2	4.0	4.6	3.2	3.6	4.8	1.6	8.0	1.8	2.2	5.4	3.0	4.6	0.0	0.0	0.0	0.4	29.4	**8.4**

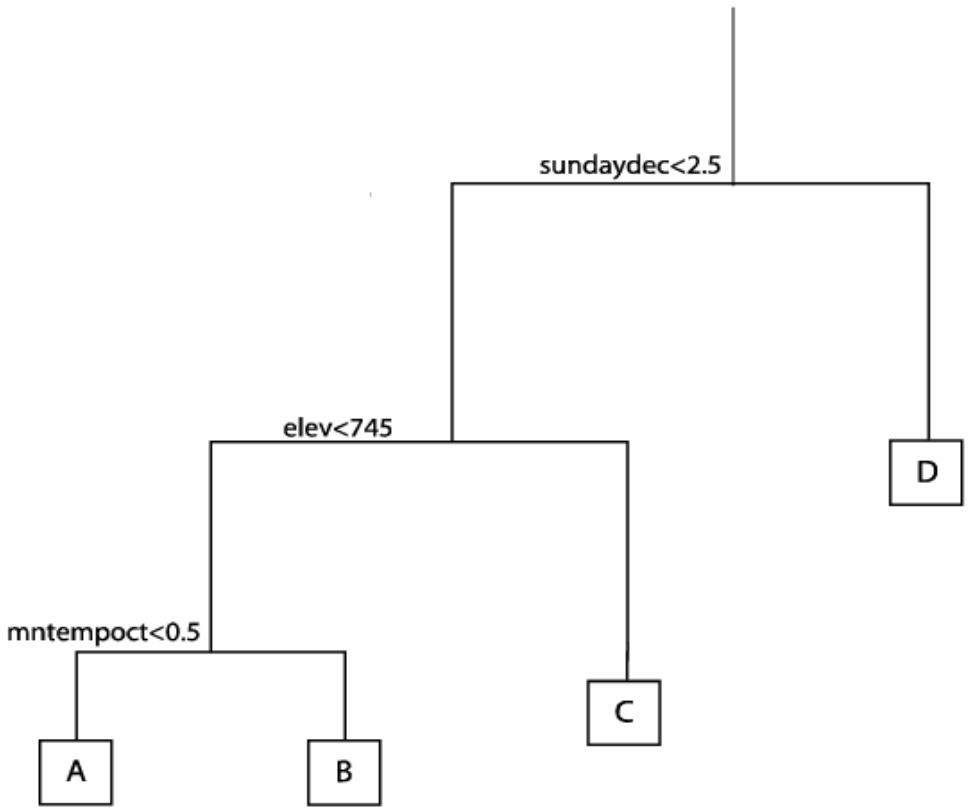

Fig. 9A. Dendrogram key for Model 1.

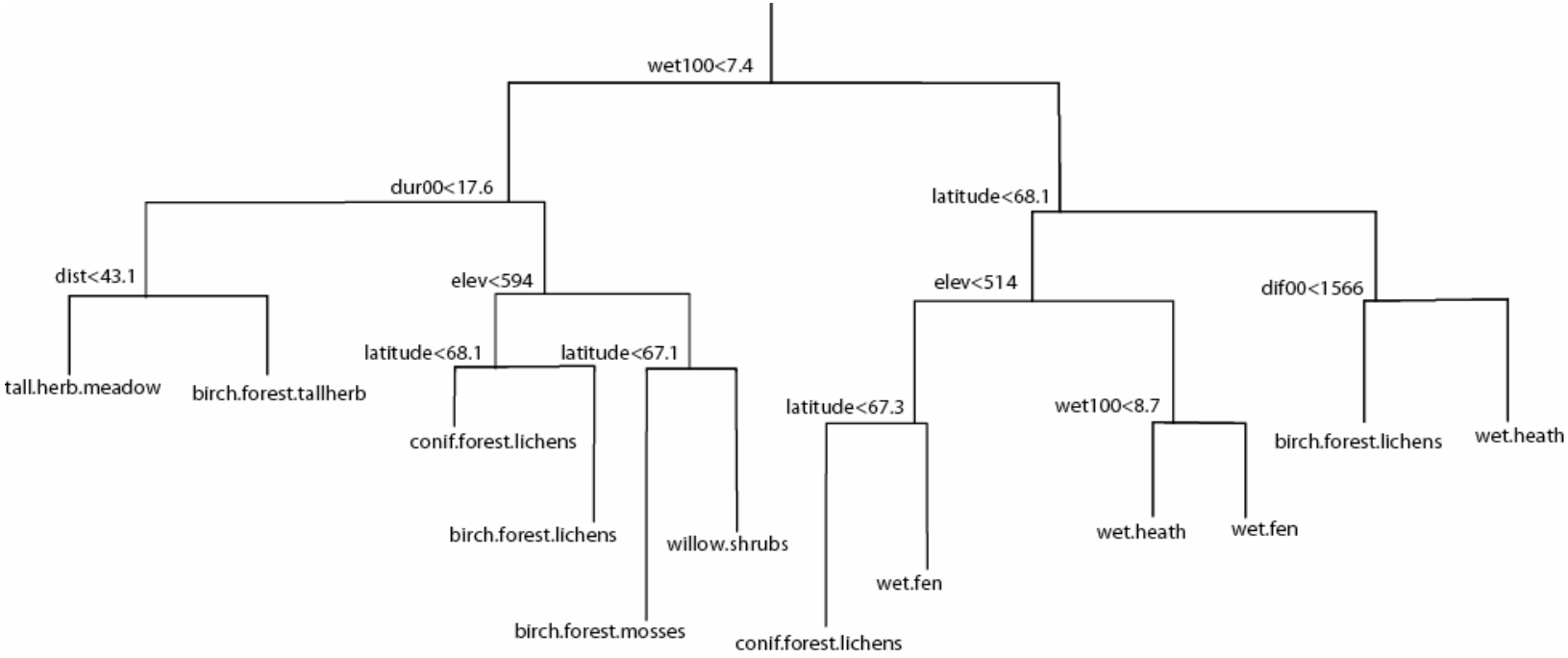

Fig. 9B. Dendrogram A for Model 1.

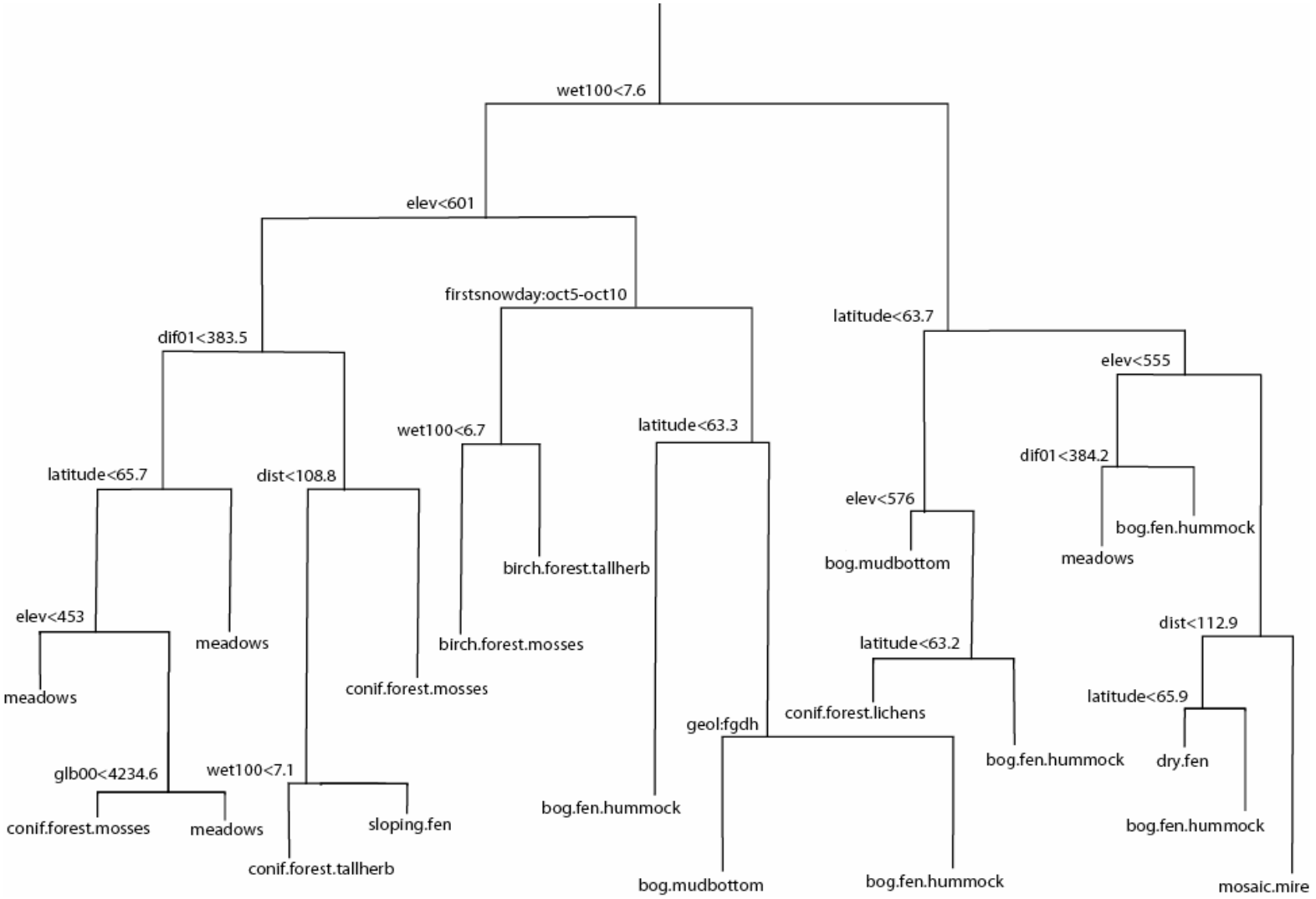

Fig. 9C. Dendrogram B for Model 1.

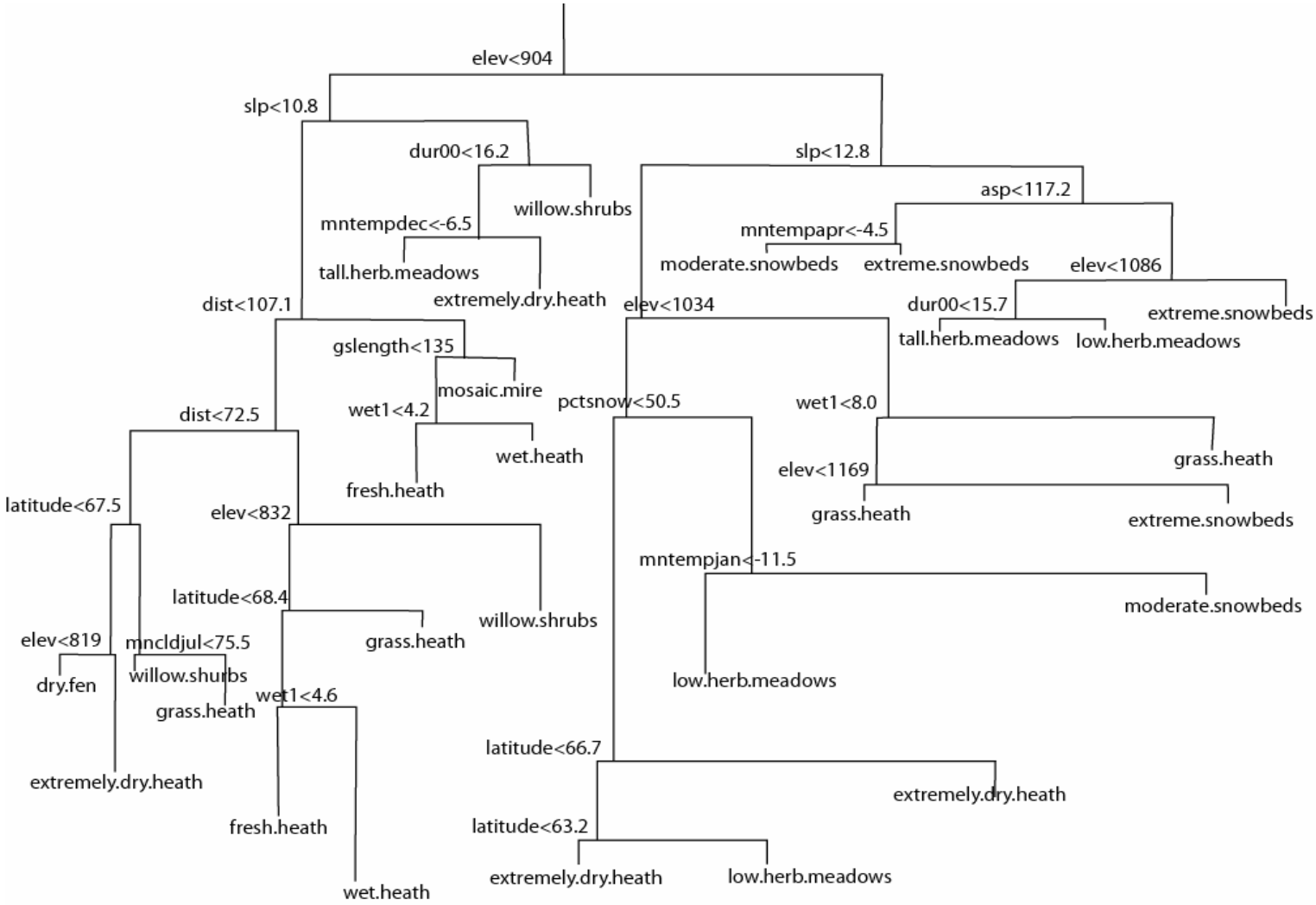

Fig. 9D. Dendrogram C for Model 1.

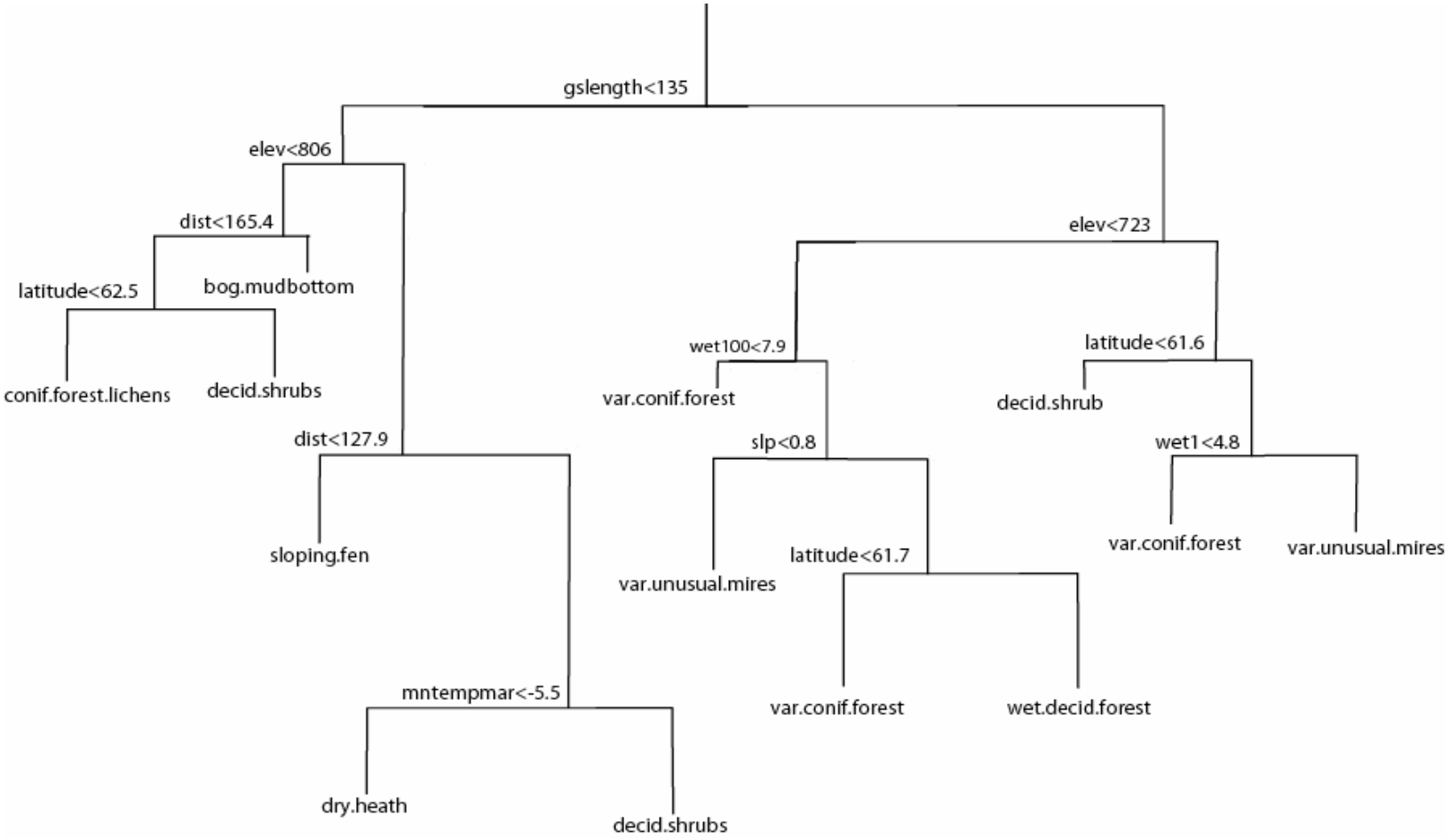

Fig. 9E. Dendrogram D for Model 1.

Table 5. Proportion of correctly predicted points of each vegetation type for Model 1.

Class	Accuracy
birch forest lichens	0.522
birch forest mosses	0.172
birch forest tall herbs	0.276
bog fen hummock	0.178
bog mud bottoms	0.698
conif forest lichens	0.614
conif forest mosses	0.268
conif forest tall herbs	0.518
deciduous shrubs	0.716
dry fen	0.112
dry heath	0.040
extreme snowbeds	0.750
extremely dry heath	0.202
fresh heath	0.080
grass heath	0.152
low herb meadows	0.196
meadows	0.444
moderate snowbeds	0.380
mosaic mire	0.400
sloping fen	0.116
tall herb meadows	0.656
var conif forest	0.472
var unusual mires	0.616
wet decid forest	0.502
wet fen	0.096
wet heath	0.410
willow shrubs	0.084

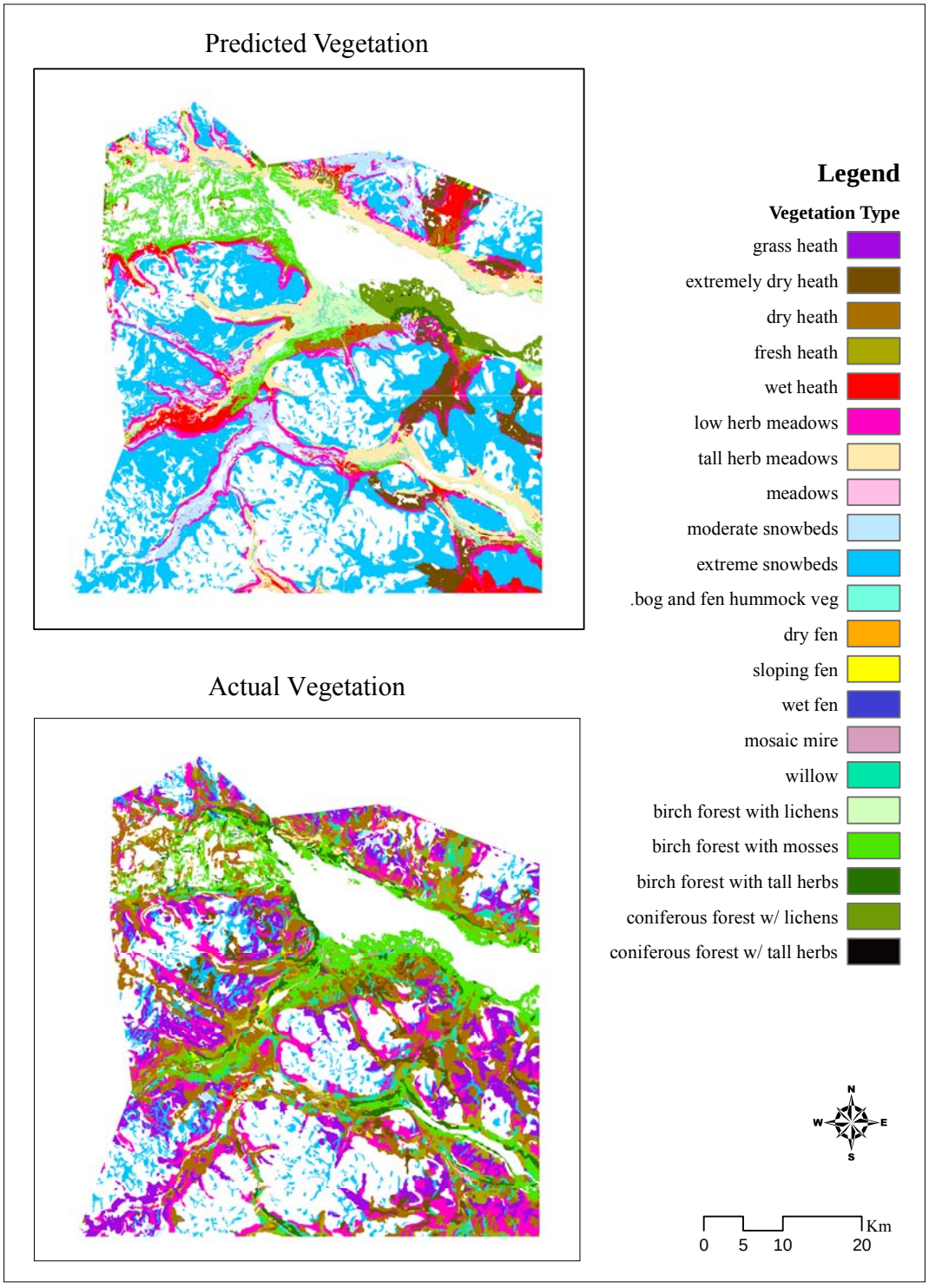

Fig. 10. Model 1 predicted vs. actual vegetation in the Abisko vegetation area.

MODEL 2

The dendrogram for Model 2 is shown in Figures 11A-D. Results of Model 2's confusion matrix (Table 6) indicate that bogs and mires, heaths, and coniferous forests were best predicted, whereas shrublands, snowbed vegetation, and meadows had the lowest predictive accuracy. Individual accuracy statistics are shown in Table 7, and a vegetation map for the Abisko area as predicted by Model 2 follows (Fig. 12).

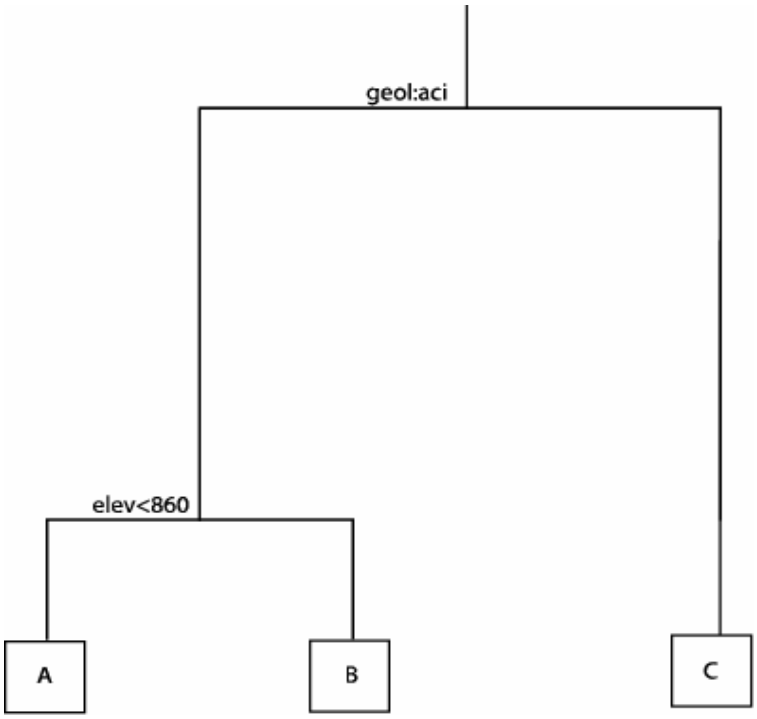

Fig. 11A. Dendrogram key for Model 2.

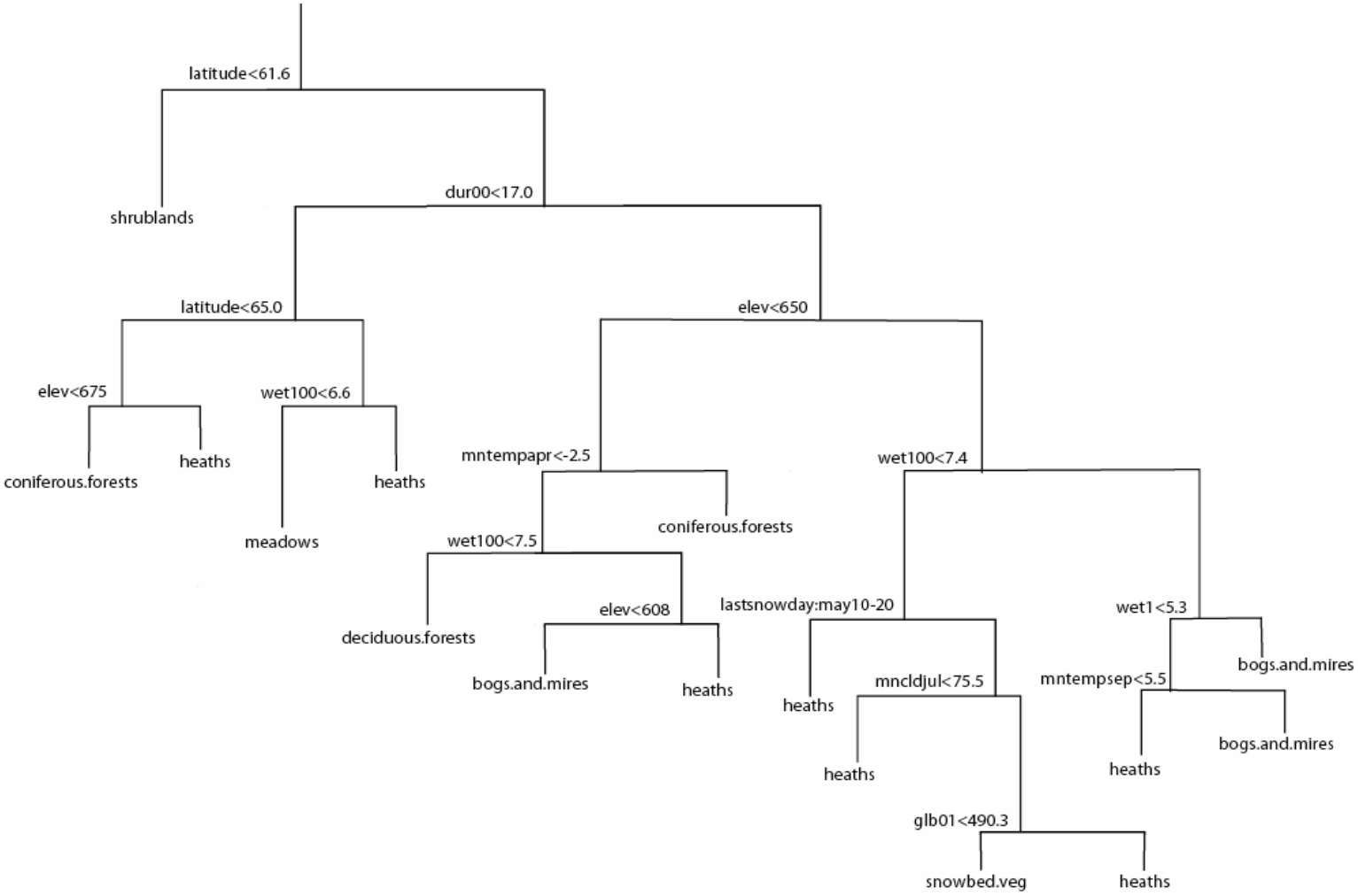

Fig. 11B. Dendrogram A for Model 2.

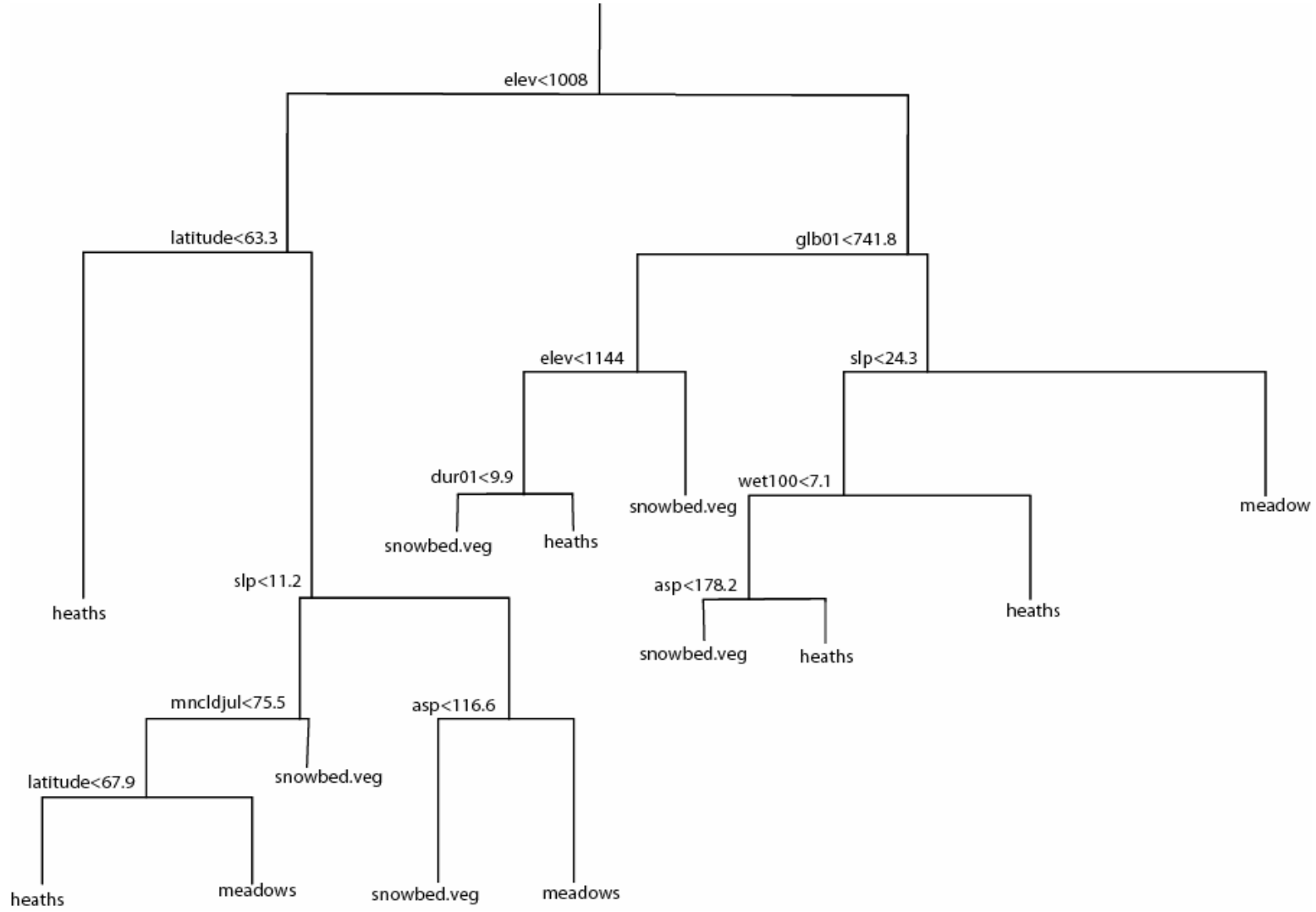

Fig. 11C. Dendrogram B for Model 2.

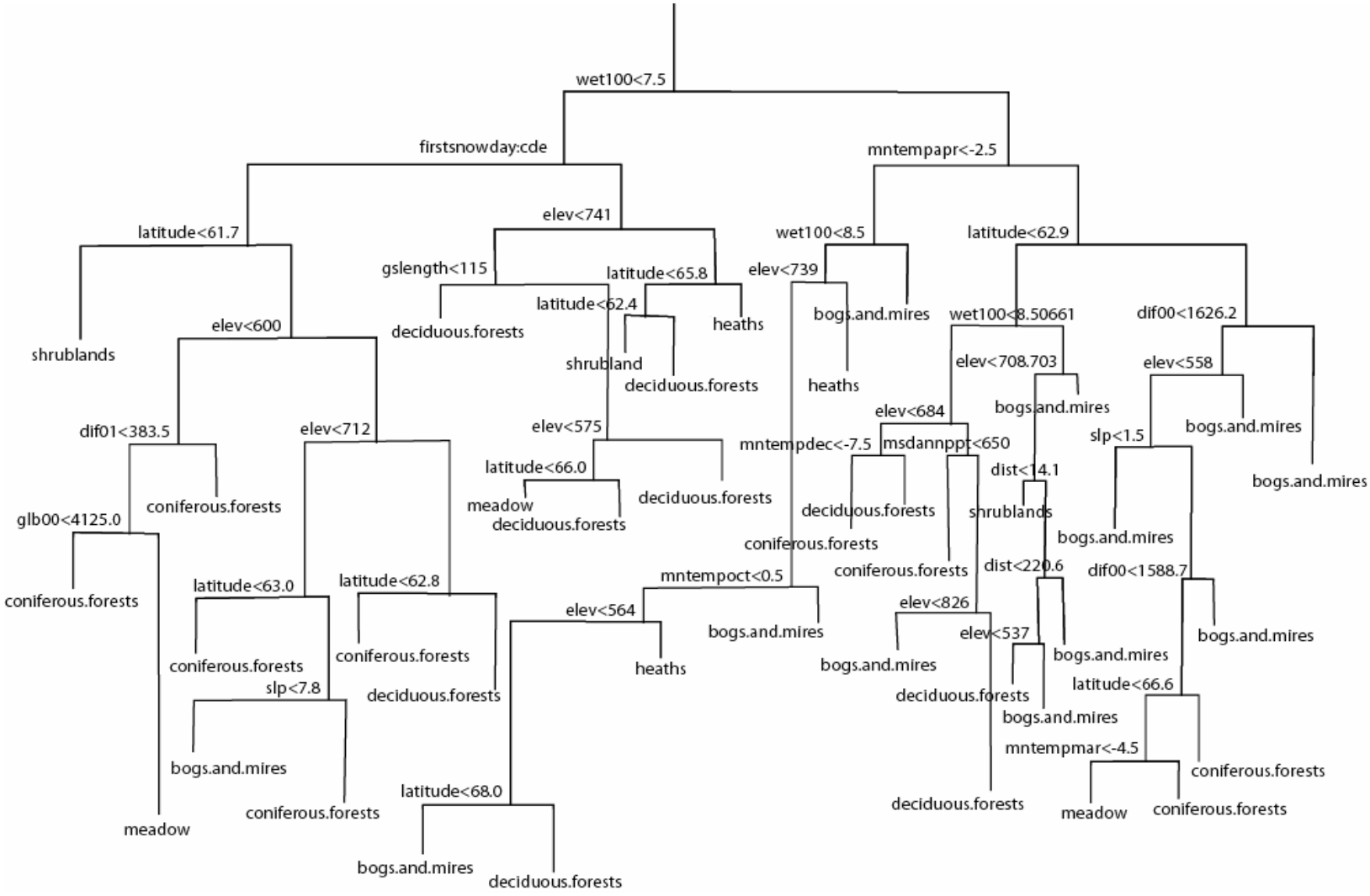

Fig. 11D. Dendrogram C for Model 2.

Table 6. Confusion matrix for Model 2. Correctly predicted vegetation types are in bold.

Predicted Veg. / Actual Vegetation	bogs and mires	coniferous forests	deciduous forests	heaths	meadows	shrublands	snowbed veg
bogs and mires	**65.0**	12.0	10.3	10.0	2.3	0.3	0.2
coniferous forests	23.0	**58.9**	9.7	1.0	6.1	1.5	0.0
deciduous forests	25.2	14.8	**45.8**	8.4	5.0	0.6	0.4
heaths	11.5	2.0	7.8	**57.4**	7.4	2.4	11.3
meadows	6.4	7.1	11.1	21.3	**46.3**	1.1	6.7
shrublands	17.4	2.5	5.8	27.8	3.4	**41.6**	1.5
snowbed veg	0.4	0.2	0.7	23.5	11.9	1.1	**62.2**

Table 7. Proportion of correctly predicted points of each vegetation type for Model 2.

Class	**accuracy**
Bogs and mires	0.650
coniferous forests	0.589
deciduous forests	0.458
heaths	0.574
meadows	0.463
shrublands	0.416
snowbed veg	0.622

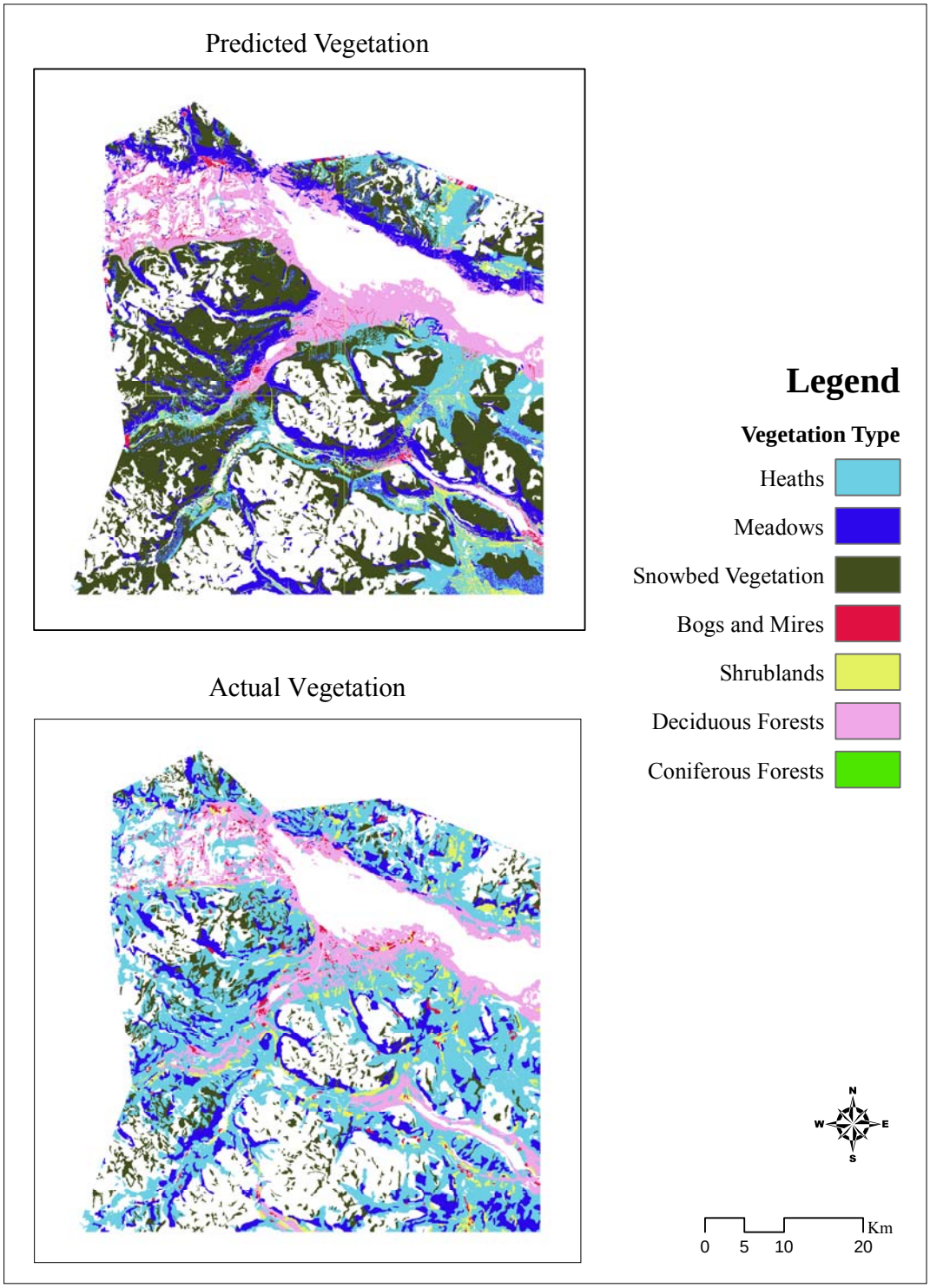

Fig. 12. Model 2 predicted vs. actual vegetation in the Abisko vegetation area.

MODEL 3

Model 3's dendrogram is illustrated in Figures 13A-D. For Model 3, the "other" category was predicted correctly the most, followed by forests and shrublands (Table 8). Table 9 illustrates individual accuracy statistics for this model, followed by Fig. 14 showing a predicted map for the Abisko vegetation area resulting from applying Model 3.

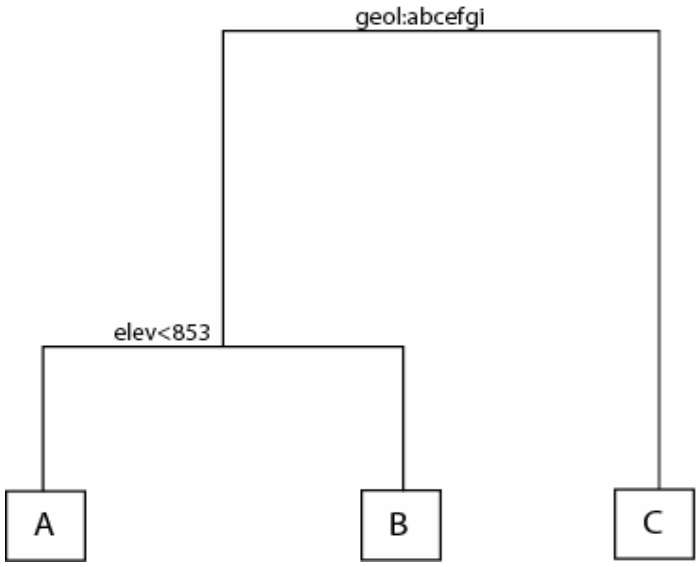

Fig. 13A. Dendrogram key for Model 3.

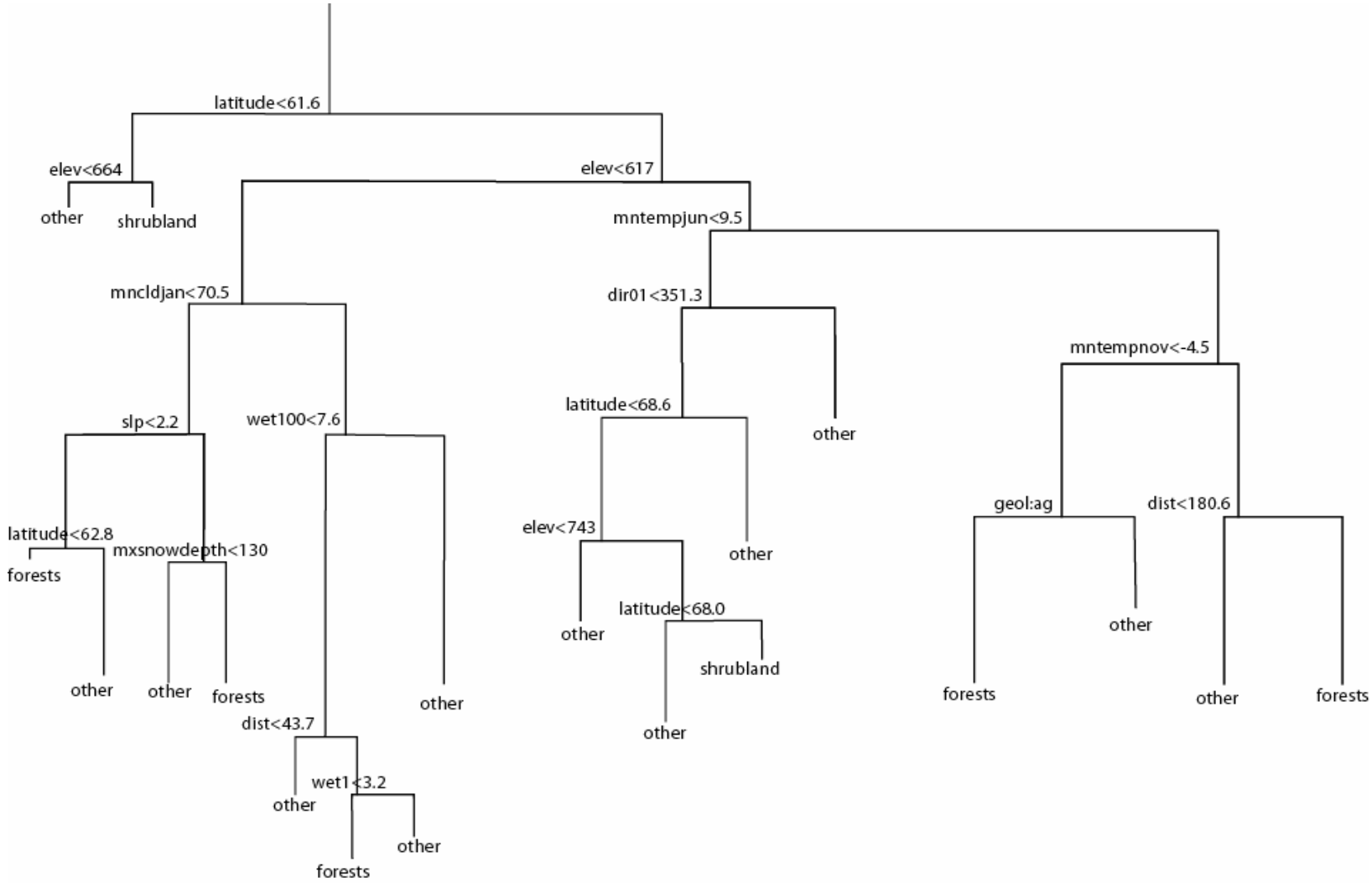

Fig. 13B. Dendrogram A for Model 3.

Fig. 13C. Dendrogram B for Model 3.

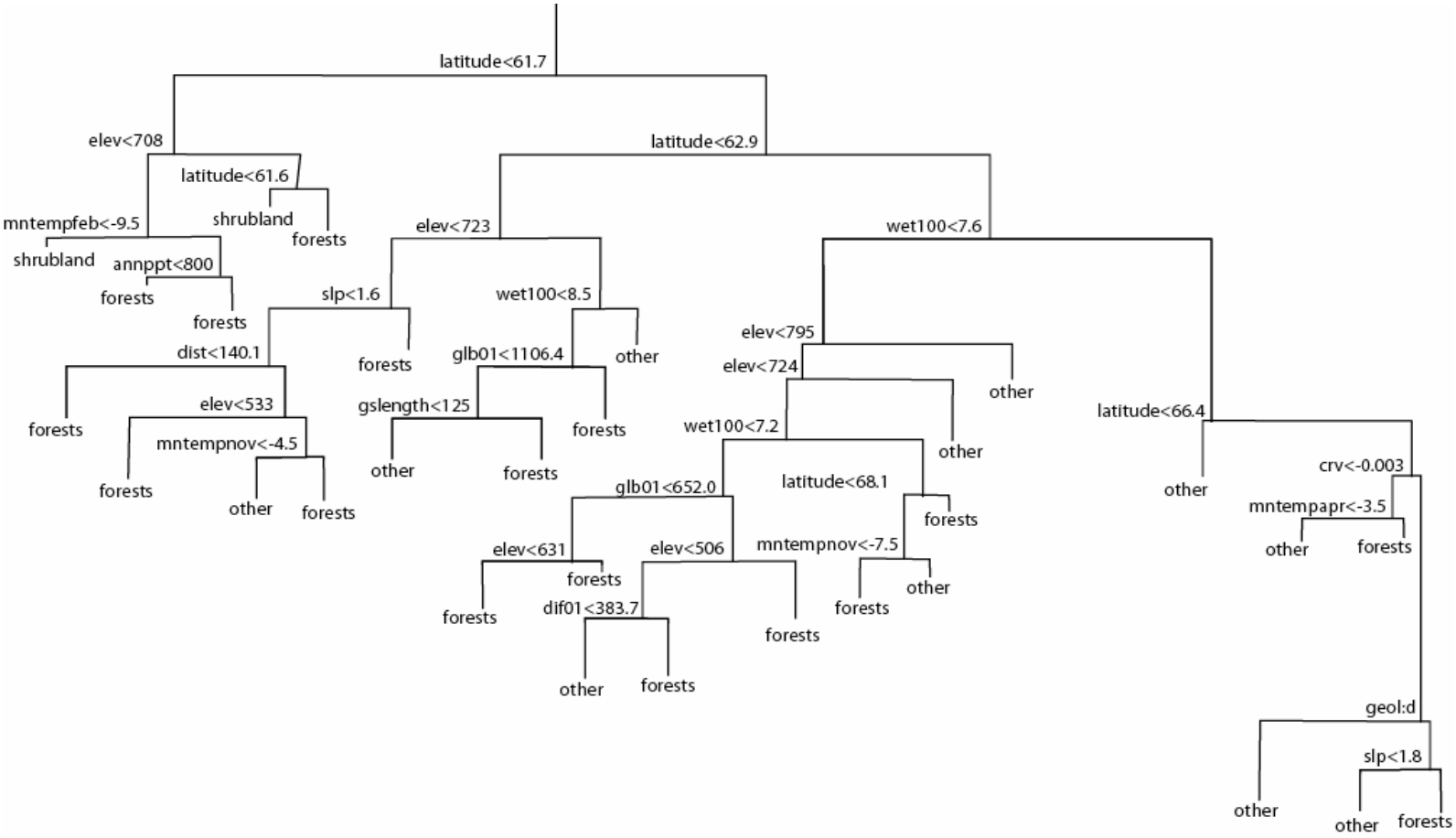

Fig. 13D. Dendrogram C for Model 3.

Table 8. Confusion matrix for Model 3. Correctly predicted vegetation types are in bold.

Predicted Veg. / Actual Vegetation	forests	other	shrublands
forests	**63.7**	34.6	1.7
other	13.1	**85.9**	1.0
shrublands	13.5	46.6	**39.9**

Table 9. Proportion of correctly predicted points of each vegetation type for Model 3.

Class	accuracy
forests	0.637
Other	0.859
shrublands	0.399

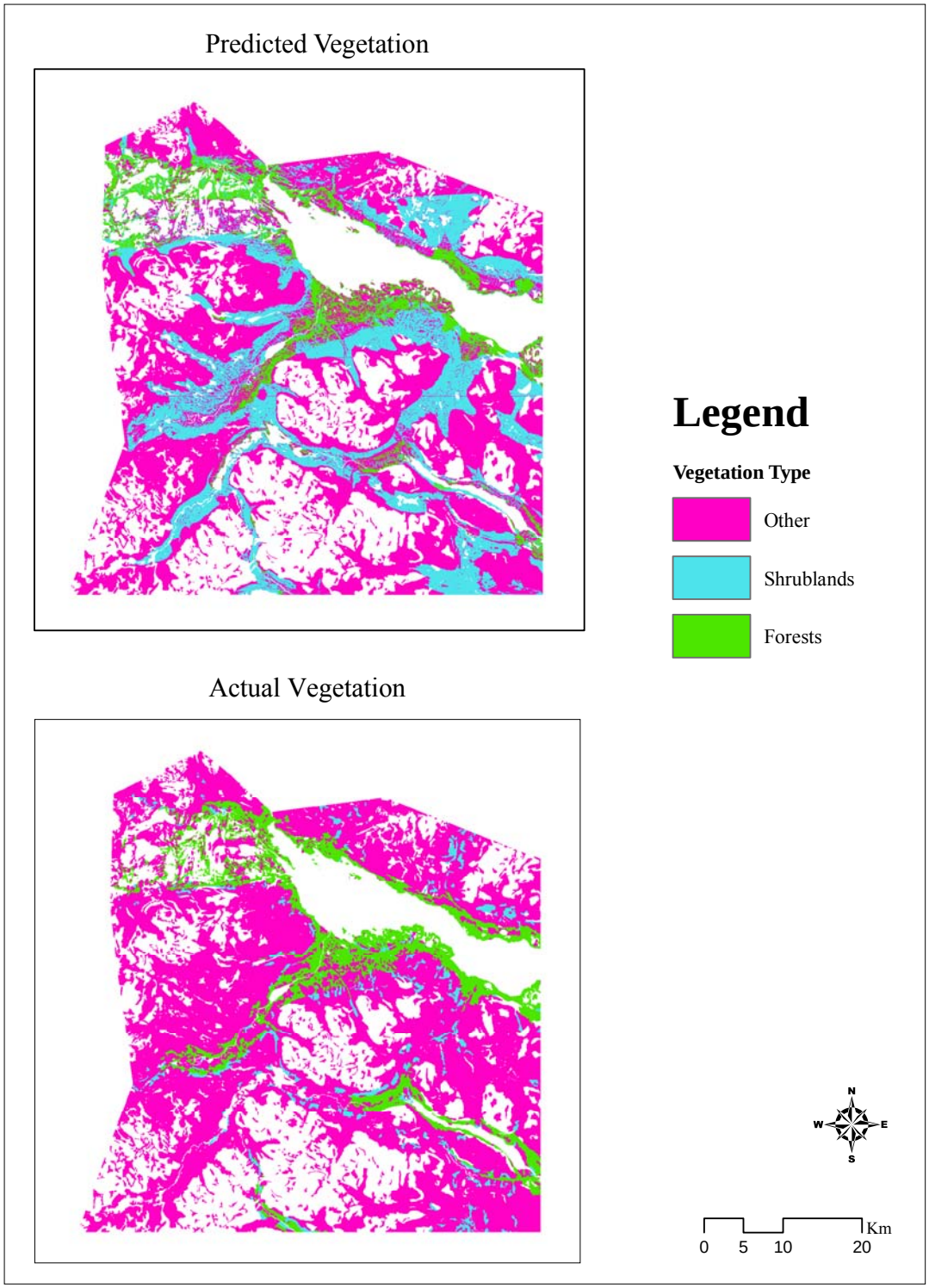

Fig. 14. Model 3 predicted vs. actual vegetation in the Abisko vegetation area.

The results from each of the three models indicate that classification tree modeling as applied to this study does better at predicting vegetation types at higher levels of aggregation of the dependent variable. For instance, the model is better at predicting the presence of forests than it is at predicting the exact type of forest (i.e. for example birch forest with lichens).

EXAMINING ECOLOGICAL RELATIONSHIPS

When conducting PVM studies, it is instructive to evaluate the extent to which the model results exhibit relationships in accordance with the scientific literature. For this study, relationships are highlighted and discussed for three specific vegetation types growing in the study area: mires, heaths & meadows, and bog vegetation. Because Model 1 incorporated the most specific (less aggregated) vegetation types, this model was thought to potentially reveal ecological relationships for specific vegetation types better than the aggregated models, and was thus the model that was examined here. As previously mentioned, mire vegetation in Sweden is thought to be dependent on hydrological factors that are mediated by topography (Sjörs 1999). To test this hypothesis, a subset of the environmental variables used in the model were targeted that encompass the hydrological and topographic factors that potentially control patterns of mire distribution: measured annual precipitation, actual precipitation, elevation, slope, aspect, curvature, landform index, and topographic wetness index. Results indicate that

several of these variables prove to be important in correlation with mire vegetation. The following table (Table 10) was derived by examining the dendrograms for Model 1. Specifically, it pulls from the dendrograms each instance where mire vegetation was classified based on splits in the dataset arising from criteria related to the suite of hydrological factors targeted. For each instance where mire vegetation was classified according to any of the hydrological factors, it was listed in the table along with the specific hydrological criteria for each split leading to the classification as mire vegetation. Table 10 also records the level of the split where the particular criteria was positioned in the dendrogram. Lower numbers indicate splits that are located higher up in the tree diagrams, and thus represent more important environmental criteria for determining vegetation distributions.

Table 10. Instances of mire vegetation occurrence in Model 1 that correlate with hydrological factors.

Instance of Vegetation Type	Environmental Criteria	Level of Split
Mosaic mires	elev < 745	2
	wet100 > 7.55	4
	elev > 555	6
Mosaic mires	elev > 745	2
	elev < 904	3
	slp < 10.8	4
Various unusual mires	elev < 723	3
	wet100 > 7.86	4
	slp < 0.8	5
Various unusual mires	elev > 723	3
	wet1 > 4.75	5

Elev= elevation; wet100= topographic wetness index with smoothing addend 100; slp= slope; wet1= topographic wetness index with smoothing addend 1

It is interesting to discover from this type of analysis that the model indicates that mire

vegetation does indeed appear to be correlated with certain hydrological factors, namely elevation, slope, and topographic wetness index, but does not appear to correlate with aspect, curvature, or landform index. Of additional interest is the fact that although elevation consistently shows up as the highest level of split in the dataset, it is not consistent in the direction of the criteria. More specifically, mosaic mires are classified at elevations above and below 745 meters at the same split level, and likewise various unusual mires are classified at above and below 723 meters in elevation at the same level of split in the tree. This seems to imply that mire vegetation is not particularly controlled by elevation, and that perhaps other factors are more important. Topographic wetness index appears to be much more consistent in the direction of influence on mire distribution. In other words, each time it shows to be a factor influencing mires, it appears that mires grow better in topographic areas where levels of moisture are above a threshold value rather than below it. As for slope, it appears to behave similarly to topographic wetness index in that the direction of the vegetation response is consistent across each occurrence of mire vegetation where slope manifests itself as a correlated factor. Specifically, mires appear to grow better below a threshold value of slope, which translates in physical terms to be areas of shallower topography. This makes sense ecologically, as mires will naturally appear in flatter areas of terrain and not on slopes.

The second vegetation type that was considered was the collective categories of heaths and meadows. Ecological literature has shown that heaths and meadows typically occur in more westerly areas where temperatures are more oceanic (Carlsson et al. 1999).

Recall that there were two different layers to represent degree of continentality: continentality (SNA dataset) and distance to coast (derived by the author). The continentality layer did not end up being used by any of the models, and so appears to be uncorrelated with the occurrence of any vegetation types, including heaths and meadows. However, the distance to coast layer did emerge as an important environmental variable. Refer to Table 11.

Table 11. Instances of heath and meadow vegetation occurrence in Model 1 that correlate with degree of continentality.

Instance of Vegetation Type	Environmental Criteria	Level of Split
Tall herb meadows	dist < 43.1	6
Extremely dry heaths	dist < 107	5
	dist < 73	6
Grass heaths	dist < 107	5
	dist < 73	6
Fresh heaths	dist < 107	5
	dist > 73	6
Wet heaths	dist < 107	5
	dist > 73	6
Grass heaths	dist < 107	5
	dist > 73	6
Dry heaths	dist > 128	4

Dist= Distance to Norwegian coastline

As shown, heaths in particular are correlated with distance to the coast, but as we have seen with prior scenarios, the direction of the response is not consistent. Heaths and meadows do appear however to locate themselves in areas where the distance to the coast is less than a threshold value more times than more. This seems not to invalidate the hypothesis that these vegetation types tend to be located in more westerly, oceanic areas of Sweden.

The third and final vegetation type that was analyzed was bog vegetation. It has been documented that bogs tend to form in wetter areas, but that vegetation in bogs tends to be limited by excessive amounts of moisture (Sjörs 1999). When testing this assertion, we might expect that the model would show bogs with vegetation to occur in areas of intermediate wetness. More precisely stated, bogs with vegetation would occur above a certain threshold value of moisture level and below a higher threshold value of moisture level. Note that the same subset of hydrological variables were isolated as for the mire vegetation already discussed. Referring to Table 12, we can see that elevation and topographic wetness index are the only two of the suite of hydrologic variables targeted.

As with mire vegetation, elevation consistently shows up at the top of the list of important variables. Unlike with the mires however, bogs are classified as occurring below 745 meters in elevation at the highest level in the tree where elevation is the criteria for the split in all but one of the instances where they occur. In other words, the response of bogs to elevation at least at the highest level of split in the tree is remarkably consistent across the range of instances where bogs occur. From these results, it is safe to say that bogs tend to form below a certain elevation. At lower levels of splits, bogs sometimes occur above a lower threshold value, which may lend support to the hypothesis that bogs tend to occur at intermediate moisture levels, because precipitation tends to be higher with increasing elevation, and this at an intermediate level at intermediate elevations. There is also a marked response of bogs to topographic wetness

Table 12. Instances of bogs with vegetation occurrence in Model 1 that correlate with hydrological factors.

Instance of Vegetation Type	Environmental Criteria	Level of Split
Bogs with fen hummocks	elev < 745	2
	wet100 < 7.55	4
	elev > 601	5
Bogs with mud bottoms	elev < 745	2
	wet100 < 7.55	4
	elev > 601	5
Bogs with mud bottoms	elev < 745	2
	wet100 > 7.55	4
	elev < 576	6
Bogs with fen hummocks	elev < 745	2
	wet100 < 7.55	4
	elev > 601	5
Bogs with fen hummocks	elev < 745	2
	wet100 > 7.55	4
	elev > 576	6
Bogs with fen hummocks	elev < 745	2
	wet100 > 7.55	4
	elev < 555	6
Bogs with fen hummocks	elev < 745	2
	wet100 > 7.55	4
	elev > 555	6
Bogs with mud bottoms	elev < 806	3

Elev= elevation; wet100= topographic wetness index with smoothing addend 100

index, but as seen previously, the relationship is not consistent in direction. It is speculative to make any clear generalizations as to why this is occurring, but it is nevertheless safe to say that topographic wetness constitutes an important split in the dataset.

FACTORS AFFECTING ACCURACY

In applications of predictive vegetation modeling, there are many possible factors affecting the accuracy of model results that need to be considered when making interpretions. Certain problems inherent with some of the specific datasets used for this study have already been discussed. This section instead focuses on factors affecting the overall accuracy of model results.

One possible source of error calls upon concepts from landscape ecology and biogeography— the ideas of scale and resolution. For clarity, scale will be defined as the spatial extent of any given phenomena of interest, while resolution will refer to the smallest unit of area where any given attribute of interest can no longer be broken down into constituent parts. Any analysis of the interaction of vegetation with its environment must involve an understanding of the importance of these two concepts.

This is because ecological processes occur at different scales (Turner et al. 2001). For example, micro-climatic processes such as changes in temperature at the ground level as a result of canopy gaps, affect underlying vegetation at a finer spatial scale than temperature fluctuations due to geographic patterns of solar insolation. Because the scale of ecological processes differs, the manifestation of these processes across geographic space occurs at different resolutions. Due to computational limitations and sampling practicalities, one cannot have both a scale as broad as the study area and data

at a fine enough resolution to represent all the ecological processes affecting the distribution and abundance of vegetation in the study area. Consequently, some ecological processes are necessarily not captured or reflected in the results of the models because the environmental data serving as the independent variables were collected or represented at too coarse of a resolution to accurately depict all the complex relationships between vegetation and its environment. Vegetation patterns reflected in the results of the models may be misleading, because some processes probably occur at a scale below the scale of the data in this study.

A related potential source of error to understand is that when multiple variables are integrated through empirical models such as classification trees, results can be questionable due to differences in the resolutions of the original environmental data (Meentemeyer et al. 2001). Any study incorporating GIS is subject to sources of error brought about by incorporating dissimilar data and attempting to synthesize it for analysis. As with all GIS applications, "error and uncertainty of various magnitudes occur when the 3-D Earth is transformed to a 2-D surface and characterized by scale and sampling resolutions defined through data generalization" (Allen et al. 2004). The data compiled for this project are characterized by varying resolutions. While specific information about the resolutions of the National Atlas of Sweden datasets was not readily available, these datasets are characterized by more coarse resolutions than the vegetation data and the data layers derived from the 50-meter resolution DEMs.

Another probable source of error deals with derivations of data resulting from interpolating, calculating, or combining. It is thought that these derivations are less accurate than the original data used to create them. Thus, "a DEM and its basic derivatives of slope, aspect, topographic position and curvature– are usually the most accurate maps available, though not necessarily those with the highest predictive potential" (Guisan & Zimmerman 2000). One way to improve accuracy of the datasets depicting the independent variables is to perform field verification on the various layers by directly observing the phenomena of interest at the study site. While this is helpful in assessing accuracy of the phenomena for which observation is possible, it cannot be done for all variables– namely for the variables which are derived rather than directly measured.

As discussed previously, there are potential problems with "static" modeling related to the assumption of equilibrium. The equilibrium concept has been criticized in the ecological literature for its failure to apply to most natural ecosystems. When vegetation is assumed to be in a state of equilibrium or quasi-equilibrium with its environment, model predictions cannot account for dynamic processes that affect vegetation such as succession following disturbances and adjustment of vegetation to climatic changes.

A final possible source of error inherent in the model that could affect the accuracy of results is the choice of which environmental variables were used to predict vegetation. It has been found that results of correlative models such as classification trees often suffer

from not including key aspects of climate that are biologically meaningful in controlling the physiological responses of plants (Neilson et al. 1992, Prentice et al. 1992). Models that incorporate environmental variables more closely related to mechanistic relationships are thought to be more valuable than those that only take into account environmental variables that are strictly correlative (Neilson et al. 1992, Prentice et al. 1992).

CONCLUSIONS

The application of predictive models of vegetation is a useful way to visualize and understand relationships between environmental parameters and distributions of vegetation types at a regional scale of analysis. However, model results should be interpreted with the understanding of the model assumptions and limitations. Future studies could expand upon the analysis here by applying Models 1, 2 and 3 to other areas within the study area to visualize the predicted vegetation patterns in different locations. Also, the results from all three models could be extended to predict expected changes in vegetation composition and structure in response to global climate change scenarios.

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